Handbook of Research on

Applied Intelligence for Health and Clinical Informatics



Anuradha Dheeraj Thakare, Sanjeev J Wagh, Manisha Sunil Bhende, Ahmed M. Anetr, and Xiao-Zhi Gao

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Handbook of Research on Applied Intelligence for Health and Clinical Informatics

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Cancer is one of the most life-threatening diseases in the world, and lung cancer is the leading cause of death worldwide. If not detected at an early stage, the survival rate of lung cancer patients can be very low. To treat patients in later stages, one needs to analyze the tumour region. For accurate diagnosis of lung cancer, the first step is to detect and segment the tumor. In this chapter, an approach for segmentation of a lung tumour is presented. For pre-processing of lung CT images, simple image processing like morphological operations is used, and for tumour segmentation task, a 3D convolutional neural network (CNN) is used. The CNN architecture consists of a 3D encoder block followed by 3D decoder block just like U-Net but with deformable convolution blocks. For this study, two datasets have been used; one is the online-available NSCLC Radiomics dataset, and the other is collected from an Indian local hospital. The approach proposed in this chapter is evaluated in terms of dice coefficient. This approach is able to give significant results with a dice coefficient of 77.23%.

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Monitoring health parameters has become a challenging task due to unpredictable diseases and related symptoms. Lifestyle is a crucial factor to decide to be healthy, in adolescent girls especially. This chapter presents a work in progress on prediction of lifestyle of adolescent girls based on problems like unhealthy routines of eating habits, sleep patterns, stress, etc. Therefore, an IT-enabled system is presented to assess current lifestyle of adolescent girls in an easy and faster way. A systematic survey is conducted with specially designed survey form by consulting medical practitioners and physical trainers. Twenty-one factors related to age, diet habits, exercise habits, sleeping habits, health history, etc. are included in the expert-guided form. One hundred fifty-five individual responses are collected and assessed manually by medical experts to annotate as healthy or unhealthy types. The healthy lifestyle prediction accuracy with support vector machine is 83.87% whereas it is 80.64% using logistic regression.

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Anxiety has been the primary cause of multiple illnesses in society. Gadgets, smartwatches, and wristbands have become an integral part of our daily lives and are widely used. This shows whether wearable sensors and technologies can be used to prevent anxiety and stress. The authors look at recent research on recognizing anxiety in everyday life in this chapter. There are few studies that examine the detection of stress in daily life, as there are few studies that examine a variety of tasks involving the recognition of anxiety in regulated laboratory settings. In this analysis, the authors isolate and examine tasks based on the physiological modality used and their intended areas, such as the workplace, education, automobiles, and the uncontrolled conditions of everyday life. In addition, they explore promising technologies, prevention, and research issues.

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Rupesh R Joshi, North Maharashtra University, India
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Medical imaging is associated with different techniques and processes that are used to create visual representations of internal parts of the human body for diagnostic and treatment purposes within digital health. Machine learning plays a crucial role in the medical imaging field including analysis of various medical images, computer-aided diagnosis or detection, image retrieval, gene data analysis, image reconstruction, and organ segmentation. The machine learning algorithm framework recognizes the best combination of the medical image features for categorizing the medical images or processing some metric for the given image area. The images obtained are then processed using algorithms such as K-means, support vector machines, decision trees, neural networks, and deep learning techniques.

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Sonali Atulkumar Patil, K. J. Somaiya College of Engineering, India
Sujata P. Pathak, K. J. Somaiya College of Engineering, India

Mental health is a major healthcare issue around the world, and it must be made a priority in the healthcare sector. That being said, it seems that progress in this area is moving at a slow rate. These conditions aren't always difficult to live with, but they also put you at risk for heart failure, severe anxiety, and depression, leading to serious stress and physical disability. In middle and upper nations, a majority of people deal with at least one of these psychiatric disorders at a certain stage in their lives. Artificial intelligence

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techniques have recently received a lot of attention in a variety of areas, including psychological health. A personalized therapy that aims to deliver emotional support to a particular person has to be enabled with the help of specialized artificial intelligence methods and ML algorithms. The aim of this chapter is to evaluate and create a system that assists a person in predicting and curing his or her psychiatric disorder using various artificial intelligence concepts and strategies, thus assisting people in curing their problems.

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Neha More, Dr. D. Y. Patil Institute of Engineering, Management, and Research, Akurdi, India
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Depression can be called a health issue that majorly affects the stability of the mind. Depression can also be called a mood disorder or mental illness that affects our mental state. Depression can affect a person mentally and physically. According to WHO, 264 million people in the world are affected because of depression. At its worst, depression can lead to suicide. About 8 million people commit suicide every year because of depression. It is not possible for one to live with depression, but if they get proper treatment at a right time, depression can be controlled and cured to help the person to live a quality life. To identify the level of depression of a person, we have to first identify the type of depression the patient is going through. The type of depression plays a very important role in determining the kind of treatment or help a depressed person needs by providing them various treatments. The authors propose a solution for detection of depression type and depression levels using advanced machine learning and artificial intelligence algorithms.

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Sagar Sudhir Dhobale, College of Engineering, Pune, India
Sharda Bapat, Algoanalytics, Pune, India

ICD (international classification of diseases) is a system developed by the WHO in which every unique diagnosis and procedure has a unique code. It provides a standardized way to represent medical information and makes it sharable and comparable across different hospitals and countries. Currently, the task of assigning ICD codes to patient discharge summaries is performed manually by medical coders. Manual coding is costly, time consuming, and inefficient for huge data. So, the healthcare industry requires automated solutions to make the medical coding more efficient, accurate, and consistent. In this study, the automated ICD-9 coding is approached as a multi-label text classification problem. A deep learning system is presented to assign ICD-9 codes automatically to the patient discharge summaries. Convolutional neural networks and word2vec model are combined to automatically extract features from the input text. The best model has achieved 83.28% accuracy. The results of this research prove the usability of deep learning for multi-label text classification and medical coding.

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Neha Motagi, Pimpri Chinchwad College of Engineering, India
Komal Nair, Pimpri Chinchwad College of Engineering, India
Rupali Narayankar, Pimpri Chinchwad College of Engineering, India

Corona is a pandemic disease and is spreading all over the world. There is also lack of corona virus detection machines. If it is detected at very early stages without pathological intervention, then further spreading of the disease can be controlled, and many of human lives can be saved. So, the proposed biomedical device can be used for fast and accurate prediction of COVID-19 from chest x-rays. X-ray can also be taken from anywhere and sent through any communication medium. Even if error is added, it can be removed using error concealment algorithms. Automated AI-based systems will be used for prediction of normal, COVID-19, and pneumonic cases from x-ray images. It makes detection of COVID-19 infection less costly and portable. This device can be stored in less stringent conditions, making it more effective.

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The COVID-19 global pandemic has affected everyone's day-to-day life. The COVID spread data is increasing rapidly which needs to be visualized in some format. The statistical data includes infected, recovered, and the death count which is visualized by various tools. This project presents an interactive dynamic dashboard to display the details about the COVID-19 patient reports, scheduled reports, timely reports, geographical reports including state-wise, district wise. It should have options to display the metrics using charts, graphs, etc. Application features include registration, download report in multiple formats, email the report, schedule a report, share a report. Users can check for Epass availability; the decision will be taken by checking the covid-affected counts on the source and destination. Patient details will be stored in the cloud. The model includes a prediction of upcoming covid-affected count using ML.

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Kevser Şahinbaş, Medipol University, Turkey

The difficult diagnosis of acute appendicitis of patients appealing to the hospital with abdominal pain often leads to unnecessary acute appendicitis operations. Accordingly, the aim of this study is to be able to provide the correct diagnosis whether the existing case indeed necessitates operation or not through machine learning algorithms based on classification. To that purpose, SMOTE, random oversampling, and random undersampling methods were proposed to reduce the negative effects of imbalanced data

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set problem on classification, and it was benefitted from the risk factors in relation to Alvarado Score to predict the diagnosis of acute appendicitis. Additionally, a classification model was generated by using support vector machine classification algorithm. A decision support system was developed that could contribute to the decision making by generating interface for support vector machine algorithm in which the best performance was obtained.

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Umesh Anandrao Patil, Shivaji University, India
Sanjeev J. Wagh, Shivaji University, India

The medical industry has advanced in a manner where high end technologies are used for early detection and analysis of diseases that are hard to encounter with normal procedures of the medical field. One such disease is diabetic retinopathy (DR) further classified as non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR) conditions. Early detection of NPDR is a challenging task, and it requires examination of fundus images in an amplified manner. To overcome these early detection of DR, the authors propose an automated system that will be using machine learning classifier techniques with combination of convolutional neural network (CNN) to self-train the system and detect the early stages of retinal scans by feature extraction and use of existing retinal scan databases. Hence, the system will eliminate the human flaw of inability to detect early DR in diagnosis and will help us treat the patient in early stages.

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Nitish Devendra Warbhe, MIT Academy of Engineering, India
Rutuja Rajendra Patil, MIT Academy of Engineering, India
Tarun Rajesh Shrivastava, MIT Academy of Engineering, India
Nutan V. Bansode, MIT Academy of Engineering, India

The COVID-19 virus can be spread through contact and contaminated surfaces; therefore, typical biometric systems like password and fingerprint are unsafe. Face recognition solutions are safer without any need of touching any device. During the COVID-19 situation as all of the people are advised to wear masks on their faces, the existing face detection technique is not able to identify the person with face occlusion. The fraudsters and thieves take advantage of this scenario and misuse the face mask, favoring them to be able to steal and commit various crimes without being identified. Face recognition methods fail to detect or recognize the face as half of the face is masked and the features are suppressed. Face recognition requires the visibility of major facial features for face normalization, orientation correction, and recognition. Thus, the chapter focuses on the facial recognition based on the feature points surrounding the eye region rather than taking the whole face as a parameter.

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Megha Sanjay Wankhade, NCRD's Sterling Institute of Management of Management Studies, India
Suhasini Vijaykumar Kottur, Bharati Vidyapeeth's Institute of Management and Technology, India

In several facets of our daily lives, including how people access and receive healthcare services, the revolutionary trend of Industry 4.0 has been introduced. The fundamental innovative structures of smart healthcare galaxies are mounting in dimensions as well as density when we change in the direction of Healthcare Industry 4.0. Aimed at creation Healthcare Industry 4.0 significant enormous, composed information are accurately treated. As per requirements in place system offer helpful knowledge in addition recommendation. Nowadays we are going into the period of imaginative specialized arrangements. These arrangements assume a significant job in the development of the country like Cyber Physical System (CPS). Cyber Physical System is using in healthcare. Today's world-wide major issues of healthcare is coronavirus disease covid-19. This study emphases on the forthcoming growth commands beneath the Industries 4.0 and highpoint precise the growth strategy of healthcare. Moreover, the security and privacy of Cyber Physical System are discussed for secure CPS System.

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Swati Ahiirao, Symbiosis International University, India
Shraddha Phansalkar, MIT-ADT University, India
Nikhil Matta, Symbiosis Institute of Technology, Symbiosis International University, India
Ketan Kotecha, Symbiosis Centre for Applied Artificial Intelligence, Symbiosis International University, India

The explosion of coronavirus has posed challenges to public health infrastructure in India. This pandemic can be contained with social distancing and isolation. The analysis of human mobility trends plays a decisive role in the spread of the pandemic. These movement patterns are extracted from Google COVID-19 Community Mobile Reports. These reports help to analyze the human mobility trends to various frequently visited places across different states of India. This work focuses on analyzing mobility trends in India and their effect on the spread of pandemic in terms of number of active cases and death rate. The mobility patterns, number of tests conducted, population density across different states in India are explored to understand their effect on the severity of epidemic. These features are correlated using statistical methods. This study lays the foundation in building a framework to contain the contributors for the spread of pandemics and provide insights to the regulatory bodies to strategize enforcing or revoking lockdown restrictions across regions in the country.

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Devidas Tulshiram Kushnure, Shri Guru Gobind Singhji Institute of Engineering and Technology, Nanded, India
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Liver segmentation is instrumental for decision making in the medical realm for the diagnosis and

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treatment planning of hepatic diseases. However, the manual segmentation of the hundreds of CT images is tedious for medical experts. Thus, it hampers the segmentation accuracy and is reliant on opinion of the operator. This chapter presents the deep learning-based modified multi-scale UNet++ (M2UNet++) approach for automatic liver segmentation. The multi-scale features were modified channel-wise using adaptive feature recalibration to improve the representation of the high-level semantic information of the skip pathways and improved the segmentation performance with fewer computational overheads. The experimental results proved the model's efficacy on the publicly available 3DIRCADb dataset, which offers significant complexity and variations. The model's dice coefficient value is 97.28% that is 7.64%, and 2.24% improved from the UNet and UNet++ model. The quantitative result analysis shows that the M2UNet++ model outperforms the state-of-the-art methods proposed for liver segmentation.

Chapter 16

Machine Learning-Aided Automatic Detection of Breast Cancer: A Survey 274

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The expeditious progress of machine learning, especially the deep learning techniques, keep propelling the medical imaging community's heed in applying these techniques in improving the accuracy of cancer screening. Among various types of cancers, breast cancer is the most detrimental disease affecting women today. The prognosis of such types of disease becomes a very challenging task for radiologists due the huge number of cases together with careful and thorough examination it demands. The constraints of present CAD open up a need for new and accurate detection procedures. Deep learning approaches have gained a tremendous recognition in the areas of object detection, segmentation, image recognition, and computer vision. Precise and premature detection and classification of lesions is very critical for increasing the survival rates of patients. Recent CNN models are designed to enhance radiologists' understandings to identify even the least possible lesions at the very early stage.

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ML-Enabled Informed Intervention for Crowdsourcing-Based Optimization of Medical Resources 291

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Ashwini Dalvi, K. J. Somaiya College of Engineering, India
Abhishek Patel, K. J. Somaiya College of Engineering, India
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Aditya S. Vedpathak, K. J. Somaiya College of Engineering, India
Viraj Thakkar, K. J. Somaiya College of Engineering, India

It is said that every adversity presents the opportunity to grow. The current pandemic is a lesson to all healthcare infrastructure stakeholders to look at existing setups with an open mind. This chapter's proposed solution offers technology assistance to manage patient data effectively and extends the hospital data management system's capability to predict the upcoming need for healthcare resources. Further, the authors intend to supplement the proposed solution with crowdsourcing to meet hospital demand and supply for unprecedented medical emergencies. The proposed approach would demonstrate its need in the current pandemic scenario and prepare the healthcare infrastructure with a more streamlined and cooperative approach than before.

Chapter 18

Prediction and Recommendation System for Diabetes Using Machine Learning Models 316

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Diabetes is one of the most deadly diseases on the planet. It is also a cause of a variety of illnesses, such as coronary artery disease, blindness, and urinary organ disease. In this situation, the patient must visit a medical center to obtain their results following consultation. Finding the right combination of characteristics and machine learning techniques for classification is also very critical. However, with the advancement of machine learning techniques, we now have the potential to find a solution to the current problem. The healthcare recommendation system (HRS) may be designed to predict health by evaluating patient lifestyle, physical health, mental health aspects using machine learning. For example, training the model using people's age and diabetes helps to predict new patients without a specific diagnostic for diabetes. The proposed deep learning model with convolutional neural network (D-CNN) achieves an overall accuracy of 96.25%. D-CNN is found to be more successful for diabetes prediction than other machine learning (ML) approaches in the experimental analysis.

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Sanjiv Patki, Prime Datamatics Inc., India
Anil Vishwanathrao Dhumma, Cellbeans Healthcare Informatics Pvt. Ltd., Pune, India
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The current coronavirus disease 2019 (COVID-19) pandemic has placed tremendous pressure on the worldwide healthcare systems. The hospitals are instructing patients to quarantine and providing medical facilities to COVID-19 patients at their homes. The feedback and proper monitoring of the quarantined patients is very important for the healthcare system. This situation has forced the use of telehealth systems to offer the delivery of medical facilities over a distance. This chapter presents a wireless telehealth system to monitor the home quarantined COVID-19 patients effectively. When an abnormality is detected then an alert is sent to the concerned hospital or doctor. The presented system allows setting the thresholds and providing alerts, reminders, and notifications to the doctors. The prototype of the presented system has been successfully developed, implemented, and tested, which helps the medical staff to monitor and treat the patients remotely, especially the coronavirus patients who are home quarantined.

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K. Bhargavi, Siddaganga Institute of Technology, India

Diabetes is one of the chronic diseases which keep increasing at an alarming rate, and the patients need to visit the clinic to routinely check their sugar levels and adjust their treatment plans. Artificial intelligence-enabled telemedicine is found to be a promising approach to monitor the health status of diabetic patients. Some of the promising artificial intelligence technologies for treating diabetic patients are a reactive machine, limited memory, theory of minds, and self-awareness. Each of these techniques is discussed with architecture, characteristics, algorithms, advantages, and applications. Performance analysis is carried out towards the performance metrics like accuracy, medical error rate, speed, and learning rate, and the performance achieved by self-awareness artificial intelligence technique is found to be better in delivering telemedicine-based care for diabetic patients with a very high level of precision

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and speed of operation.

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Towards an Effective Imaging-Based Decision Support System for Skin Cancer 354
Ricardo Vardasca, Instituto Superior de Gestão e Administração, Santarém, Portugal
Carolina Magalhaes, Institute of Science and Innovation in Mechanical and Industrial Engineering, Portugal

The usage of expert systems to aid in medical decisions has been employed since 1980s in distinct applications. With the high demands of medical care and limited human resources, these technologies are required more than ever. Skin cancer has been one of the pathologies with higher growth, which suffers from lack of dermatology experts in most of the affected geographical areas. A permanent record of examination that can be further analyzed are medical imaging modalities. Most of these modalities were also assessed along with machine learning classification methods. It is the aim of this research to provide background information about skin cancer types, medical imaging modalities, data mining and machine learning methods, and their application on skin cancer imaging, as well as the disclosure of a proposal of a multi-imaging modality decision support system for skin cancer diagnosis and treatment assessment based in the most recent available technology. This is expected to be a reference for further implementation of imaging-based clinical support systems.

Chapter 22
Web-Based Machine Learning Application for Heart Disease Prediction: Machine Learning in the Healthcare Industry 383
Lokesh M. Giripunje, Dr. D. Y. Patil Institute of Engineering, Management, and Research, Akurdi, India
Tejas Prashant Sonar, Dr. D. Y. Patil Institute of Engineering, Management, and Research, Akurdi, India
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Jayant C. Modhave, Dr. D. Y. Patil Institute of Engineering, Management, and Research, Akurdi, India
Mahesh B. Gaikwad, Dr. D. Y. Patil Institute of Engineering, Management, and Research, Akurdi, India

Risk because of heart disease is increasing throughout the world. According to the World Health Organization report, the number of deaths because of heart disease is drastically increasing as compared to other diseases. Multiple factors are responsible for causing heart-related issues. Many approaches were suggested for prediction of heart disease, but none of them were satisfactory in clinical terms. Heart disease therapies and operations available are so costly, and following treatment, heart disease is also costly. This chapter provides a comprehensive survey of existing machine learning algorithms and presents comparison in terms of accuracy, and the authors have found that the random forest classifier is the most accurate model; hence, they are using random forest for further processes. Deployment of machine learning model using web application was done with the help of flask, HTML, GitHub, and Heroku servers. Webpages take input attributes from the users and gives the output regarding the patient heart condition with accuracy of having coronary heart disease in the next 10 years.

Chapter 23

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Web-Based Modernized Architecture Over Cloud Computing for Facial Extraction and Recognition 394
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Web content is diverse and is regarded as the primary source of accessible information that can be accessed through reference links. Web facial images are one type of web content that relates to important web pages and is considered important information for individuals. This chapter proposes face recognition as a service architecture that is based on real-world images from the web. The proposed service is implemented as a service for other third parties via cloud computing; additionally, its architecture is built via cloud using virtual machines that can be expanded based on resource demands. Web crawlers crawl web pages and retrieve images for elastic cloud storage. The collected images are then used to remove human faces and prepare the face images for identification and identifying the matched face of the set through successive phases. This chapter used PCA for features extraction and KNN for identification. Experiments show that increasing the number of crawler instances improves crawling speed and improves face recognition accuracy by preferring Euclidean over other metrics.

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Preface

The applied intelligence concerns to ability of a machine to learn the way a human learns. For example, through neural networks and discovering patterns in complex situations, machines able to recognize possible symptoms. The applied intelligence in health care and clinical informatics domain shaping advance level of disease diagnosis and treatments by the way information gets collected, analyzed and developed for patient care. The stakeholders working in health care and administration are increasingly vital to the operation of any sizable health care issues using applied intelligence. The medical professionals are uniquely taking steps into important roles in the field areas with multi-directional thinking, and their services are shaping the ways health and clinical informatics is changing with experience.

The efficient usage of available resources and advance therapy to combat chronic diseases is challenging tasks. The health professionals around the world are facing challenges in accepting to advanced technologies for disease diagnosis and treatments. Parallel to challenges, there is an increasing tendency for new methodologies and applications development to improve healthcare service quality, to reduce costs and to make people more prosperous.

The book provides a broad collection of methodologies, approaches, tools and techniques for modeling and solving complex real-world health problems. Some of the approaches helps to transform imperfect data into mathematical shape using soft computing techniques. The applied intelligence for health care and clinical informatics covers various components i.e. telemedicine, public health, hospital managements with their crucial sub units such as intensive care units, operation theatre room, laboratories, emergency room, etc.

The informatics domain within the field of public health is a developing and growing industry. Clinical informatics are used in direct patient care by supplying medical practitioners with information that can be used to develop a care plan. Intelligent applications in clinical informatics facilitates with the technology-based solutions to analyze data or medical images and help clinicians to retrieve that information. Decision models aid with making complex decisions especially in uncertain situations.

The book is a comprehensive reference materials that focuses on the study of resources and methods for the management of healthcare infrastructure and information. This book provides insights on how applied intelligence with deep learning, experiential learning, and more will impact healthcare and clinical information processing. The content explores the representation, processing, and communication of clinical information in natural and engineered systems.

This book covers a range of topics including applied intelligence, medical imaging, tele-health, and decision support systems, and also looks at technologies and tools used in the detection and diagnosis of medical conditions such as cancers, diabetes, heart disease, lung disease, and prenatal syndromes. It is an essential reference source for diagnosticians, medical professionals, imaging specialists, data spe-

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cialists, IT consultants, medical technologists, academicians, researchers, industrial experts, scientists, and students.

To satisfy the target audience and to meet the challenges, we have scrutinized the best 23 chapters in health care and clinical informatics domain which directly focuses on emergent issues and way to resolve the issues by applying various methodologies and techniques:

In the first chapter, Shweta Tygi et al proposed a novel approach of lung tumor segmentation using a 3D Deep Convolutional Neural Network. In this chapter, an approach for segmentation of lung tumor is presented. For pre-processing of lung CT images, simple image processing like morphological operations are used and for tumor segmentation task, a 3D convolutional neural network (CNN) is used. The CNN architecture consists of a 3D encoder block followed by 3D decoder block just like U-Net, but with deformable convolution blocks. For this study, two datasets have been used, one is online available NSCLC Radiomics dataset and another is collected from an Indian local hospital. The approach proposed in this chapter is evaluated in terms of dice coefficient.

In the second chapter, Anuradha Thakare et al. focus on an intelligent approach for prediction of life style conditions in adolescent girls by analyzing health parameters. This chapter presents work-in-progress on prediction of lifestyle of adolescent girls based on problems like unhealthy routines of eating habits, sleep patterns, stress etc. Therefore, IT-enabled system is presented to assess current lifestyle of adolescent girls in easy and faster way. A systematic survey is conducted with specially designed survey form by consulting medical practitioner and physical trainer. 21 factors related to age, diet habits, exercise habits, sleeping habits, health history etc are included in expert-guided form. 155 individual responses are collected and assessed manually by medical experts to annotate as healthy or unhealthy type.

In the third chapter, Bhupendra Ramani et al. explores study on anxiety detection using physiological data and wearable IoT devices. The study focus on recent research on recognizing anxiety in everyday life in this article. There are few studies that examine the detection of stress in daily life and examine a variety of tasks involving the recognition of anxiety in regulated laboratory settings. In this analysis, authors isolate and examine tasks based on the physiological modality used and their intended areas, such as the workplace, education, automobiles, and the uncontrolled conditions of everyday life.

In the fourth chapter, Deepti Nikumbh et al. proposed applied intelligence for medical diagnosing. The proposed approach recognizes the best combination of the medical image features for categorizing the medical images or processing some metric for the given image area. The images obtained are then processed using algorithms such as K-means, support vector machines, decision trees, neural networks and deep learning techniques.

In the fifth chapter, Kartik Desai et al. developed an Intelligence for Mental Health Detection: Mano Vaidya – A mental health therapist. The proposal expert system focus on a personalized therapy that aims to deliver emotional support to a particular person has to be enabled with the help of specialized artificial intelligence methods and ML algorithms. The chapter evaluate and create a system that assists a person in predicting and curing his or her psychiatric disorder using various artificial intelligence concepts and strategies, thus assisting people in curing their problems.

In the sixth chapter, Suvarna Patil et al. presents artificial intelligence and machine learning based advanced depression detection system. The proposal focus on depression management. To identify the level of depression of a person, first identify the type of depression the patient is suffering. The type of depression plays a very important role in determining the kind of treatment or help a depressed person needs by providing them various treatments. The author proposed a solution for detection of depression type and depression levels using advanced machine learning and artificial intelligence algorithms.

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In the seventh chapter, Sagar Dhobale and Sharda Bapat proposed an automated ICD Coding using deep learning system. A deep learning system is presented to assign ICD-9 codes automatically to the patient's discharge summaries. Convolutional neural networks and word2vec model are combined to automatically extract features from the input text. The results of this research prove the usability of deep learning for multi-label text classification and medical coding.

In the eighth chapter, Rajani P.K. et al. introduce autonomous smart device for COVID-19 detection using artificial intelligence. The proposed biomedical device can be used for fast and accurate prediction of COVID-19 from chest X-rays. X-ray can also be taken from anywhere and send it through any communication medium. Even if error is added, it can be removed using Error concealment algorithms. Automated AI based system will be used for prediction of Normal, COVID-19 and Pneumonic cases from each X-ray images. Besides, it makes detection of COVID-19 infection, which is cost efficient and portable. This device can be stored in less stringent conditions, making it more effective.

In the ninth chapter, Manisha Bhende et al. studied COVID-19 data forecasting and spread visualization using machine learning. This chapter presents an interactive dynamic dashboard to display the details about the Covid19 patients reports, scheduled reports, timely reports, geographical reports includes state-wise, district wise. Also have options to display the metrics using charts, graphs, etc. Application features include registration, download report in multiple formats, email the report, schedule a report, and share a report. Users can check for E-pass availability, the decision will be taken by checking the COVID affected counts on the source and destination. Patient details will be stored in the cloud. The model includes a prediction of upcoming COVID affected count using machine learning.

In the tenth chapter, Kevser Şahinbaş focuses on decision support proposal for imbalanced clinical data. The author propose SMOTE, Random Oversampling and Random Under sampling methods to reduce the negative effects of imbalanced data set problem on classification and it was benefitted from the risk factors in relation to Alvarado Score to predict the diagnosis of acute appendicitis. Additionally, a classification model was generated by using Support Vector Machine classification algorithm. A decision support system was developed that could contribute to the decision-making by generating interface for Support Vector Machine algorithm in which the best performance was obtained.

In the eleventh chapter, Umesh Patil and Sanjeev Wagh introduce a method for detection of diabetic retinopathy using convolutional neural network and multiple classifier techniques using machine learning approach. The diabetic retinopathy disease classified as non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (DR) conditions which are caused by diabetes. Early detection of NPDR is a challenging task and it requires examination of fundus images in a amplified manner. To overcome these early detection of DR we are proposing a automated system that will be using machine learning classifier techniques with combination of convolutional neural network to self-train the system on its own and detect the early stages of retinal scans by feature extraction and use of existing retinal scan databases. Hence the system will eliminate the human flaw of inability to detect early DR in diagnosis and will help us treat the patient in early stages itself.

In the twelfth chapter, Nitish Warbhe et al. dealt with face detection with face mask for Covid-19 pandemic using neural networks. During the covid-19 situation as all of the people are advised to wear masks on their face the existing face detection technique is not able to identify the person with face occlusion. The fraudsters and thieves take advantage of this scenario and misuse the face mask, favoring them to be able to steal and commit various crimes without being identified. Face recognition methods fails to detect or recognize the face as half of the face is masked and the features are suppressed. Face recognition requires the visibility of major facial features for face normalization, orientation correction,

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and recognition. Thus the chapter focuses on the facial recognition based on the feature points surrounding the eye region rather than taking whole face as a parameter.

In the thirteenth chapter, Megha Wankhede and Suhasini Kottur explores Healthcare and Cyber Physical System. The authors introduce the revolutionary trend industry 4.0 in commercial contexts. The fundamental innovative structures of Smart Healthcare galaxies are mounting in dimensions as well as density when change in the direction of Healthcare Industry 4.0. Aimed at creation Healthcare Industry 4.0 significant enormous, composed information are accurately treated. As per requirements in place system offer helpful knowledge in addition recommendation.. The study emphases on the forthcoming growth commands beneath the Industries 4.0 and highpoint precise the growth strategy of healthcare. Moreover, the security and privacy of Cyber Physical System are discussed for secure CPS System.

In the fourteenth chapter, Swati Ahiirao et al. explore the impact of human mobility trends on the outbreak of COVID-19 across different states of India. The analysis of human mobility trends plays a decisive role in the spread of pandemic. These movement patterns are extracted from Google COVID-19 Community Mobile Reports. These reports help to analyze the human mobility trends to various frequently visited places across different states of India. This work focuses on analyzing mobility trends in India and their effect on the spread of pandemic in terms of number of active cases and death rate. The mobility patterns, number of tests conducted, population density across different states in India are explored to understand their effect on the severity of epidemic. These features are correlated using statistical methods. This study lays foundation in building a framework to contain the contributors for the spread of pandemics and provide insights to the regulatory bodies to strategize enforcing or revoking lockdown restrictions across regions in the country.

In the fifteenth chapter, Devidas Kushnure and Sanjay Talbar introduce M2UNet++ A Modified Multi-Scale UNet++ Architecture for Automatic Liver Segmentation in Computed Tomography Images. The chapter presents the deep learning-based modified multi-scale UNet++ (M2UNet++) approach for automatic liver segmentation. The multi-scale features modified channel-wise using adaptive feature recalibration to improve the representation of the high-level semantic information of the skip pathways and improved the segmentation performance with fewer computational overheads. The experimental results proved the model's efficacy on the publicly available 3DIRCADb dataset, which offers significant complexity and variations.

In the sixteenth chapter, M. Abdul Jawad and Farida Khursheed survey Machine Learning aided automatic detection of breast cancer. The expeditious progress of machine learning especially the deep learning techniques keep propelling the medical imaging community`s heed in applying these techniques in improving the accuracy of cancer screening. Among various types of cancers breast cancer is the most detrimental disease affecting women today. The prognosis of such types of disease becomes very challenging task for radiologists due the huge number of cases together with careful and thorough examination it demands. The constraints of present CAD open up a need for new and accurate detection procedures. Deep Learning approaches have gained a tremendous recognition in the areas of object detection, segmentation, image recognition and computer vision. Precise and premature detection and classification of lesions is very critical for increasing the survival rates of patients. Recent CNN models are designed to enhance radiologist`s understanding to identify even the least possible lesions at the very early stage.

In the seventeenth chapter, Irfan Siddavatam et al. dealt with ML Enabled Informed Intervention for crowdsourcing based optimization of medical resources. The chapter proposed technology assistance to manage patient data effectively and extends the hospital data management system's capability to predict the upcoming need for healthcare resources. Further, the authors intend to supplement the proposed

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solution with crowdsourcing concept to meet hospitals demand and supply for unprecedented medical emergencies. The proposed approach would demonstrate its need in the current pandemic scenario and prepare the healthcare infrastructure with a more streamlined and cooperative approach than before.

In the eighteenth chapter, Nareshkumar Mustar and PhaniKumar Singamsetty proposed prediction and recommendation system for diabetes using machine learning models. Finding the right combination of characteristics and machine learning techniques for classification is critical. However, with the advancement of Machine Learning techniques, now have the potential to find a solution to the current problem; The Healthcare Recommendation System (HRS) may be designed to predict health by evaluating patient lifestyle, physical health, and mental health aspects using machine learning. Example, training the model using people's age and diabetes helps to predict new patients without a specific diagnostic for diabetes. The proposed Deep Learning Model with Convolutional Neural Network (D-CNN) achieves better accuracy. D-CNN is found to be more successful for diabetes prediction than other Machine Learning (ML) approaches in the experimental analysis

In the nineteenth chapter, Vijay Mane et al. explore Tele-health System for Effective Treatment in Covid-19 Pandemics. This chapter presents a wireless Tele-health system to monitor the home quarantined COVID 19 patients effectively. When an abnormality is detected then an alert is sent to the concerned hospital or doctor. The presented system allows to set the thresholds, provide alerts, reminders, and notifications to the doctors. The prototype of the presented system has been successfully developed, implemented and tested, which helps the medical staff to monitor and treat the patients remotely, especially the coronavirus patients who are home quarantined.

In the twentieth chapter, K. Bhargavi present Telemedicine based Diabetic Care Powered with Artificial Intelligence. Artificial intelligence-enabled telemedicine is found to be a promising approach to monitor the health status of diabetic patients. Some of the promising artificial intelligence technologies for treating diabetic patients are a reactive machine, limited memory, theory of minds, and self-awareness. Each of these techniques is discussed with architecture, characteristics, algorithms, advantages, and applications. Performance analysis is carried out towards the performance metrics like accuracy, medical error rate, speed, and learning rate, and the performance achieved by self-awareness artificial intelligence technique is found to be better in delivering telemedicine-based care for diabetic patients with a very high level of precision and speed of operation.

In the twenty-first chapter, Ricardo Vardasca and Carolina Magalhaes explores an effective imaging-based decision support system for skin cancer. The literature provides background information about skin cancer types, medical imaging modalities, data mining and machine learning methods and their application on skin cancer imaging, as well as the disclose of a proposal of a multi-imaging modality decision support system for skin cancer diagnosis and treatment assessment based in the most recent available technology. This is expected to be a reference for further implementation of imaging based clinical support systems.

In twenty-second chapter, Lokesh Giripunje et al. introduce web-based machine learning application for heart disease prediction. The prediction of heart diseases at early stage gives the insight to doctor to take necessary action on patient. The optimized solution using machine learning in healthcare helps to analyze the tons of data & provide precise outcomes. The deployment of machine learning model on webpage is executed within proposed framework. Webpage take input attributes from the user and gives the accuracy in prediction of heart disease.

In twenty-third chapter, Mohamed ElSayed ElAraby and Ahmed M. Anter proposed Web-based Modernized Architecture over Cloud Computing for Facial Extraction and Recognition: Web-based

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Modernized Architecture over Cloud Computing for Facial Extraction and Recognition. This chapter proposes a face recognition as a service architecture that is based on real-world images from the web. The proposed service is implemented as a service for other third parties via cloud computing; additionally, its architecture is built via cloud using virtual machines that can be expanded based on resource demands. Web crawlers crawl web pages and retrieve images for elastic cloud storage. The collected images are then used to remove human faces and prepare the faces images for identification and identifying the matched face of the set through successive phases. This chapter used PCA for features extraction, and KNN for identification. Experiments show that increasing the number of crawler instances improves crawling speed and improves face recognition accuracy by preferring Euclidean over other metrics.

We would like to compliment the authors for publishing their original work to this book. We also present our special gratitude to the reviewers who devoted their time selflessly and helped improve the overall quality of the chapters. We hope that this book will provide new insights to the readers and stimulate further work in health care and clinical informatics.

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Chapter 1
A Novel Approach of Lung Tumor Segmentation Using a 3D Deep Convolutional Neural Network

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ABSTRACT

Cancer is one of the most life-threatening diseases in the world, and lung cancer is the leading cause of death worldwide. If not detected at an early stage, the survival rate of lung cancer patients can be very low. To treat patients in later stages, one needs to analyze the tumour region. For accurate diagnosis of lung cancer, the first step is to detect and segment the tumor. In this chapter, an approach for segmentation of a lung tumour is presented. For pre-processing of lung CT images, simple image processing like morphological operations is used, and for tumour segmentation task, a 3D convolutional neural network (CNN) is used. The CNN architecture consists of a 3D encoder block followed by 3D decoder block just like U-Net but with deformable convolution blocks. For this study, two datasets have been used; one is the online-available NSCLC Radiomics dataset, and the other is collected from an Indian local hospital. The approach proposed in this chapter is evaluated in terms of dice coefficient. This approach is able to give significant results with a dice coefficient of 77.23%.

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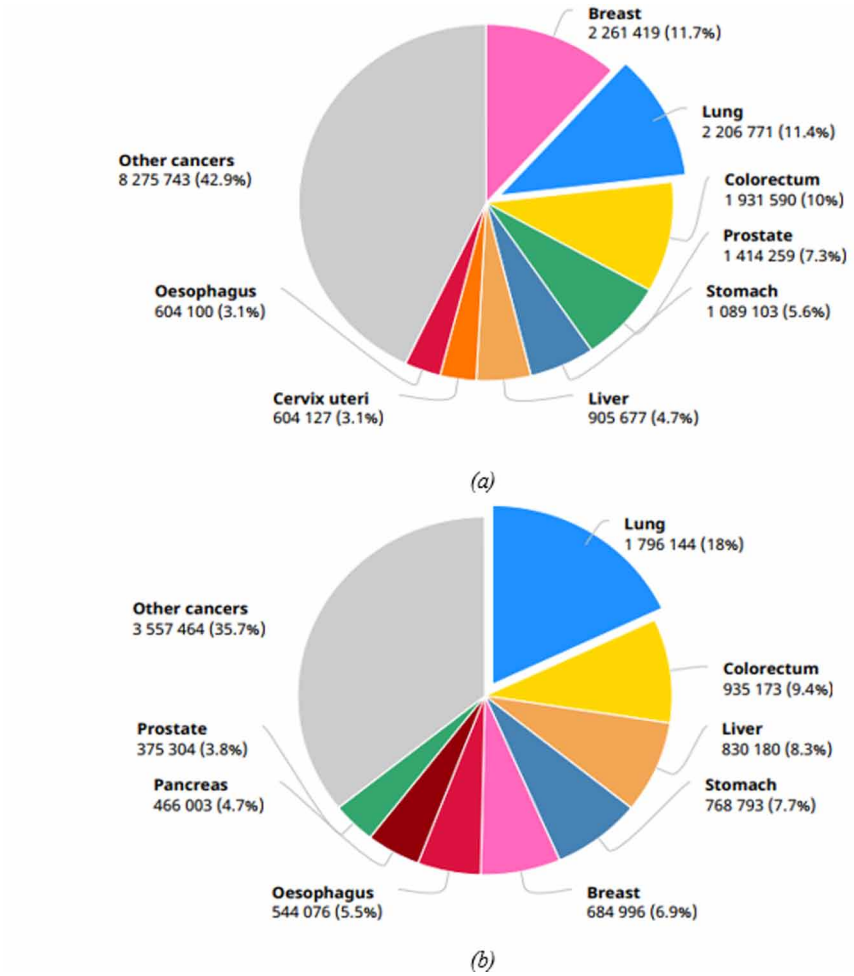
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INTRODUCTION

Cancer is a deadly disease with total cases 1,92,92,789 and 99,58,133 deaths in 2020 according to GLOBOCAN report 2020. It is a disease in which abnormal cells divide in an uncontrolled manner and can spread to nearby tissues through the process of metastasis. Lung Cancer is the most common diagnosed cancer among all other types of cancer, and is the leading cause of cancer deaths worldwide, with incidence rate 11.4% (2206771 cases) and mortality rate 18% (1796144 deaths), according to GLOBOCAN report, 2020 and India lies in South-eastern Asia where total lung cancer cases in 2020 were 1,23,309 and 1,09,520 deaths due to lung cancer (Source: GLOBOCAN 2020). The statistics is shown in Figure 1. Lung Cancer patients can be diagnosed with the help of different imaging tests like, X-rays, CT-scans, PET-scans etc. but CT scan is preferred because CT scans can give information about the specific features of the tumor, including its shape, size, location and internal density and are more accurate than chest x-rays in determining the nature of the tumor.

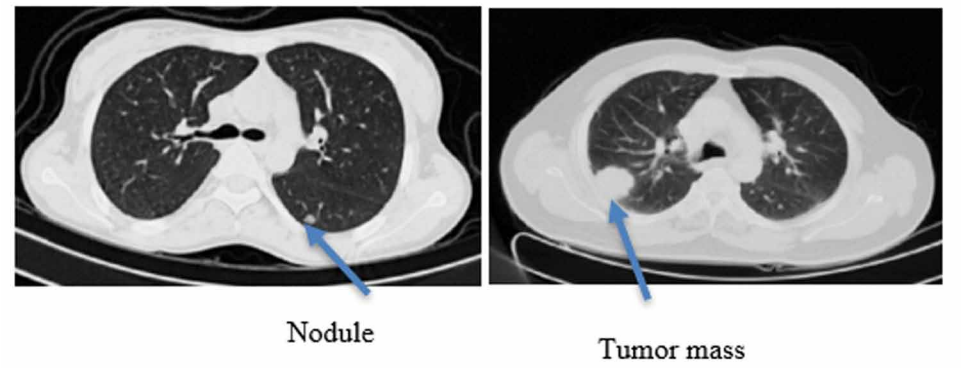
Figure 1. Pie charts showing (a) Incidence rate and (b) Mortality rate of different cancers across world-wide across the globe, Source: (Ferlay 2020)



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The treatment of Lung Cancer and survival of patients depends on several factors like its size, type, stage and patients' response to a specific treatment. To increase the survival rate, it is important to detect the cancer at an early stage. For early-stage detection of Lung Cancer, the nodule (size less than 30mm) detection is necessary, but it is mostly diagnosed in its later stages when treatment becomes difficult and chances of survival are less. And if it is not detected in early stages then it may spread to other parts of the body via metastasis and in that case the size of tumor (size more than 30mm) increases which needs to be detected and analyzed. This will assist the doctor in decision making for a specific treatment plan, to increase the survival rate of the patient. The tumor analysis task is divided into several sub-tasks which include tumor segmentation, detection and classification. In this chapter, a 3D Convolutional Neural Network (CNN) for the initial subtask in analysis of tumor that is tumor segmentation, is proposed. For this purpose, the authors have collected lung cancer CT image data from an Indian Hospital (Tata Memorial Hospital, Mumbai, India) and also used an online accessible dataset named NSCLC Radiomics. The CT image with nodule (size<30mm) and CT image with tumor mass (size>30mm) are shown in Figure 2.

Figure 2. CT images, left showing nodule and right showing tumor mass



The rest of the chapter is organized as, first, the background and related work regarding lung data and lung image processing, is presented, second, proposed research methodology is explained, third, results are discussed, fourth, the future directions are provided and finally the chapter is concluded in fifth section.

BACKGROUND AND RELATED WORK

A. Lung Image Datasets

Several lung image datasets are publicly available on online platforms. These datasets include data for lung or lung lobes segmentation like LObe and Lung Analysis 2011 (LOLA 11) dataset which is a part of a challenge, data for lung nodule analysis like LIDC-IDRI (Gray 2011), LNDb (Pedrosa 2019) and data for lung tumor analysis like structseg (which is a part of a challenge), NSCLC Radiomics (Aerts, 2019) etc.

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B. Lung Nodule Segmentation Using CNNs

Artificial Intelligence (AI) and Deep Learning have proved their significance by providing promising results in various fields including the field of Medical Image Processing. The main advantage of deep convolutional neural network is that once the network is trained with a good amount of annotated data, the trained network then, can be used to test the unseen data and a large amount of data can be tested at once with no much hardware requirements (only during training, there is hardware requirements to solve a huge number of computations). Various Deep Convolutional Neural Network architectures are designed by researchers like AlexNet (Alex, 2012), VGGNet (Liu, 2015), ResNet (He, 2016) etc. which outperformed in several computer vision tasks. Deep CNNs have also provided state-of-the-art performance in the medical imaging field. Ronneberger et al. designed a special network called UNet specifically for medical image segmentation (Ronneberger 2015). R Sathishkumar et al. used KNN algorithm and SVM classifier for lung cancer detection and classifying whether the image is normal or there is a tumor (Kumar, 2019). Many of the researchers worked for the analysis of lung nodules like Setio et al. designed a deep learning algorithm for detection of lung nodules and false positive reduction (Setio, 2016). They used a multi-view Convolution Neural network and LIDC-IDRI dataset for training and validation. They achieved the sensitivity level of 90.1% for 4 false positives. Wenkai Huang et al. proposed a noisy U-net for detection of lung cancer nodules using CT images and they have used leaky ReLU activation function. Noisy U-Net (NU-Net) is an improved version of U-Net in which a special noise is added to the hidden layers in training so that the network's sensitivity to small nodules can be enhanced (Huang, 2019). They trained the network using the LUNA 16 (LUng Nodule Analysis 2016) dataset and Alibaba Tianchi Lung Cancer Detection Competition dataset. They made a comparative analysis between U-Net and NU-Net, which reveals that the proposed algorithm attained greater sensitivity i.e., 97.1% to small nodules with diameters of 3–5 mm than the U-Net value i.e., 90.5%. Different variants of UNets are used by researchers for various medical image processing task including lung images, like in (Tong, 2018; Zhao, 2018; Xiao, 2020). Ganesh Singadkar et al. propose a DDRN (Deep Deconvolutional Residual Network) based algorithm for lung nodule segmentation. They trained this network on 2D CT images made the network able to capture the diversity of the nodules from CT images (Singadkar, 2020). They have used summation-based long skip connection between convolutional and deconvolutional part of the network which preserves the spatial information that was lost during the pooling operation and captures the high-resolution features. The dataset used in this work is Lung Image Database Consortium and Image Database Resource Initiative (LIDC/IDRI) dataset and this approach achieved average Dice scores of 94.97%, and Jaccard index of 88.68%. Wangxia Zuo et al. used multiresolution CNN (MRCNN) for lung nodule classification using CT images (Zuo, 2019). This neural network is able to extract features of different levels and resolutions from several depth layers of the network for classification of lung nodules. They transferred the knowledge from the source network model which was applied for edge detection and then improved the model to a multi-resolution model which was perfect for the nodule classification task. The LUNA16 dataset was used by the authors and results show that their method attains an accuracy of 0.973, precision of 0.967, and an AUC of 0.995, which is greater than the scores obtained by many the state-of-the-art methods. The algorithms which are used for lung nodule segmentation may not work well with large and irregular size tumor segmentation, because the networks in these algorithms are trained with nodule data so they have learnt the features of nodules which are comparatively having smaller size as compared to tumor. Therefore, for lung tumor segmentation we require more robust algorithms which can learn the features of large size tumors.

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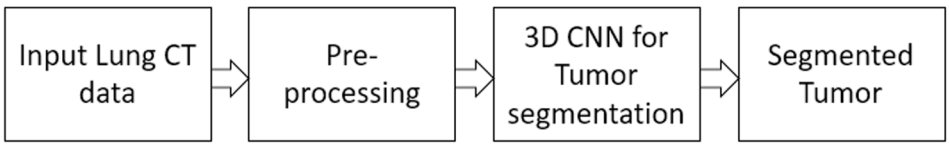
C. Lung Tumor Segmentation Using CNNs

For tumor detection using Deep Learning, there is scarcity of literature. Selin Uzelaltinbulat et al. used image processing techniques for tumor segmentation (Uzelaltinbulat, 2017) They used Median filtering for image smoothing and Otsu thresholding for the segmentation task. M. Anthimopoulos et al. proposed an algorithm using Convolutional Neural Network with dilated filters (Anthimopoulos, 2019). The network proposed by them is popularly known as 2D LungNet. The dilation filters are used to increase the receptive field of the feature maps and helps in high resolution precision. The similar approach but with 3D network is proposed by S. Hossain et al. in which they utilized a dilated hybrid 3D CNN architecture which is also named as 3D LungNet, for tumor segmentation (Hossain, 2019). from 3D lung CT scans which were taken from the NSCLC-Radiomics Dataset. First, a binary classifier is used to select CT scan slices which contain parts of a tumor. To segment the tumorous region, the selected CT slices are passed to the segmentation model which by using dilated convolutions, extracts feature maps from each 2D slice and then combines the stacked maps via 3D convolutions - incorporating the 3D structural information present in the CT scan volume into the output. Then, the predicted segmentation masks are passed through a post-processing mechanism to get cleaned through morphological operations. This segmentation model outperformed other models like LungNet and U-Net by achieving average and median dice coefficient on the test set 65.7% and 70.39% respectively which is greater than LungNet with dice scores of 62.67% and 66.78%. A recurrent 3D DenseUNet architecture was proposed by Kamal et al. (Kamal, 2020). They have used UNet like encoder-decoder structure with one modification that they used a recurrent block in between encoder and decoder, which consisted of multiple ConvLSTM (Convolutional Long Short-Term Memory) layers. In encoder and decoder, they have used densely connected 3D convolutional layers, which helps the network to enable feature aggregation through out the network. They experimented their approach on NSCLC-radiomics dataset, and achieved a dice score of 0.75. All these proposed networks are good but some are having limitations to segment the irregular shape of the tumor. To solve this problem, the authors have proposed the deformable convolution-based CNN.

Research Methodology

The methodology is divided into three subtasks which are Image acquisition, Pre-processing and Tumor segmentation and the flowchart of complete process is shown in Figure 3.

Figure 3. A block diagram of proposed methodology



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A. Image Acquisition

The lung cancer image database was collected from the Tata Memorial Hospital, Mumbai, India and another dataset used in this work is publicly available dataset NSCLC Radiomics. The data collected from local hospital consists a total of 370 CT scans which consist of both baseline (pre-treatment) and post treatment CT scans, out of which 220 CT scans are selected after data cleaning. Out of these 220 CT scans, 130 baseline CT scans are selected such that no patient is repeated. 100 baseline CT scans are used for training, and remaining 30 CT scans for testing the proposed 3D CNN. The NSCLC Radiomics consists of a total of 422 patients. The data is in the format of RTSTRUCT (DICOM Radiotherapy Structure Sets) and DICOM Segmentation files contain a manual delineation of the 3D volume of the primary gross tumor volume (GTV-1), out of this dataset, 372 patients are used for training and 50 for validation purpose. The description of dataset used for training and testing, is given in Table 1.

Table 1. Dataset description

	NSCLC	Local Hospital dataset
For Training (472)	372	100
For testing (80)	50	30

During training of the network, training errors such as overfitting or underfitting can cause problem in designing a robust model. Overfitting of a CNN occurs when the network is achieving a very good training accuracy but does not generalize well on the test data, and gives a very low accuracy. And underfitting is a situation where the network neither performs well on training data nor on test data. To prevent overfitting and underfitting, several techniques can be implemented like cross-validation, data augmentation, early stopping etc. In the proposed approach, the authors have used cross-validation and early stopping. For cross-validation, the training data (472 CT scans) is divided into training (400 CT scans) and validation dataset (72 CT scans). And for testing, remaining 80 CT scans are used.

B. Pre-Processing

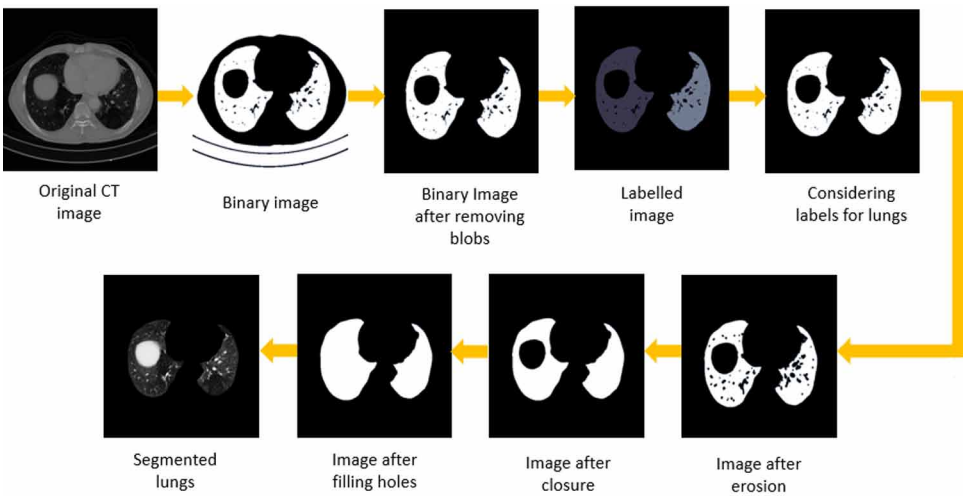
Pre-processing of the images is required before performing the tumor analysis because sometimes the dataset which is obtained from the hospital, consists of images with poor contrast which will not provide good results without some preprocessing. And, lung segmentation is required, because a lung CT image also contains other organs. Convolutional Neural Networks work on pixel level and transform the pixels into a meaningful information. If more pixels from the unwanted part of the image are available then the CNN will unnecessarily take extra processing parameters which in turn, will increase the training time. So, it is essential to segment the lungs in the CT image so that more accurate results can be obtained. For preprocessing both simple image processing techniques and Convolutional Neural Networks may be used based on their accuracy. Due to unavailability of lung segmentation masks which is required for CNN to train, the authors have used simple image processing techniques such as thresholding and morphological operations, which provide good results. As also explained in (Tripathi 2019), marker-

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controlled watershed segmentation provides better results for nodule segmentation. In this work, the authors have used this phenomenon for lung field segmentation.

In the preprocessing task, first the intensity values in the CT images are clipped into the desired intensity range for the lung tumor segmentation task, which is -1000 Hounsfield Unit (HU) to +1000 HU range, and then scaled between 0 and 1. For the process of lung segmentation, a threshold is applied on the input CT image to get the binary image, then the blobs connected to the lungs are removed in the binary image. Then the labels are given to the different areas in the image, after which only largest areas that is lungs are kept in the image. Then erosion and closing operations are performed to get only the region of interests in the image, after the holes are filled and the lung mask is generated which when superimposed on the original image and considering all other values to zero, provides the segmented lung images. The flow of this process is shown in Figure 4. And the lung segmentation results are presented in Figure 5.

Figure 4. Overview of lung segmentation algorithm

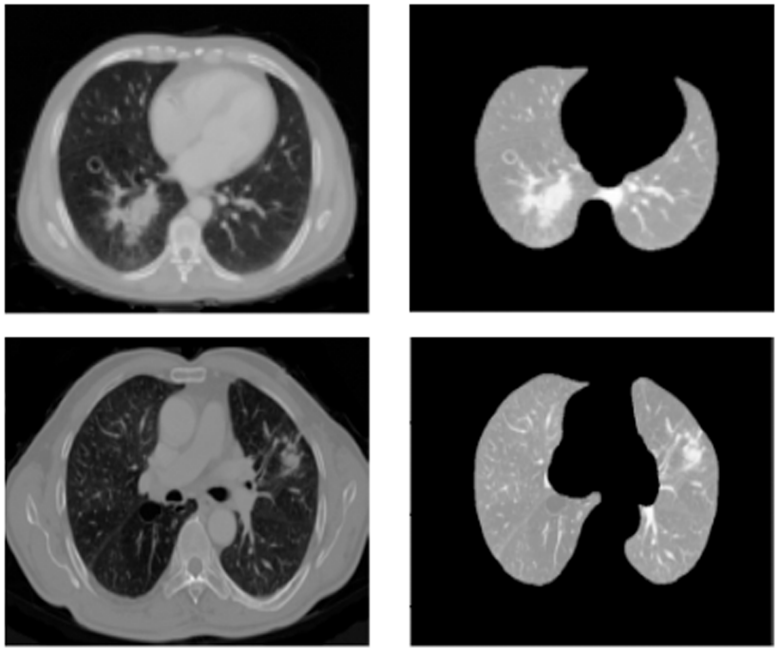


C. Tumor Segmentation

For performing tumor segmentation, a 3D Convolutional Neural Network has been proposed in this chapter. The proposed 3D CNN consists of an encoder-decoder structure like U-Net proposed in (Ronneberger 2015), in which encoder is used for capturing the context and decoder enables the precise localization. The novelty of the proposed method lies in the facts that, the authors have used deformable convolution in both encoder and decoder and batch normalization (BN) followed by ReLu in each convolution and deformable convolution block. First, the authors are segmenting the lungs from the CT scans and then applying these segmented 3d images of size 256×256 as input to CNN. Thus, by applying only necessary part of the image that is segmented lungs to CNN improves the learning capability of the network specifically to the lung region and makes the computations relatively faster. Second, BN helps the network to train faster and makes it easier to initialize the weights, and Third they have using the local hospital dataset for training and testing the network.

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Figure 5. Lung segmentation results (a) Input CT image and (b) corresponding output image with segmented lungs



i. Deformable Convolution

Deformable convolution is defined as a process in which deformable kernel is used, which has learnable shape to work for changes and unknown complex transformations in input features. In standard convolution, the shape of kernels is fixed from the starting, which is defined by sampling matrix. In the input feature map, different locations may correspond to objects with varying scales and deformation for which fixed receptive field may not work accurately, that is why the need of deformable convolution arises. The process of deformable convolution is generally divided into two steps. The first step is to obtain the offsets by learning from the bypass convolution. And then second step is to adopt bilinear interpolation to determine the value of sampling points. Consider grid R representing the size and dilation of the receptive field and R={(-1, -1), (-1, 0),…..,(1, 0), (1, 1)}, defines a 3 × 3 kernel. $x(p_0+p_n)$ represents the various locations of the input feature map, $\omega(pn_)$, weight of the convolution kernel and $y(p0_)$, the different locations of the output feature map. According to the convolution principle, for each location Po of the output feature map Y can be represented as shown in equation (1)

$$y\left(p_0\right)=\sum_{p_n\in R}\omega\left(p_n\right)*x\left(p_0+p_n\right) \tag{1}$$

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In deformable convolution, consider the input feature map with shape (a × h × w × c), and the values with shape (a × h × w × 2c) are obtained by bypass convolution, which is known as offset field, and here 2c is representing the offsets in both x and y directions. After the bypass convolution, these offsets are added with the sample points over the input feature map to change the convolution position, so that the convolution process is more suitable for the object of interest. The equation for deformable convolution can be written as shown in equation (2) where Δp_n represents the offsets which are added to the normal convolution operation to get the deformable convolution.

$$y(p_0) = \sum_{p_n \in R} \omega(p_n) * x(p_0 + p_n + \Delta p_n) \tag{2}$$

The receptive field of deformable convolution is deformed by using the offset field. And this deformed receptive field can learn the size and scale variations present in the image and helps in getting better segmentation results. Figure 6. shows how the deformed receptive field is generated from the previous layer with the help of offset filed and shows how the output feature map is generated using both 2D and 3D deformable convolution operation. And Figure 7. shows that as compared to the standard convolution, the sample points generated by deformable convolution are irregular as required to segment the irregular shape of tumor more accurately. In deformable convolution, instead of using fixed sample matrix, the learnable sample matrix is used which is learnt from location offsets and these offsets are learnt from preceding feature maps.

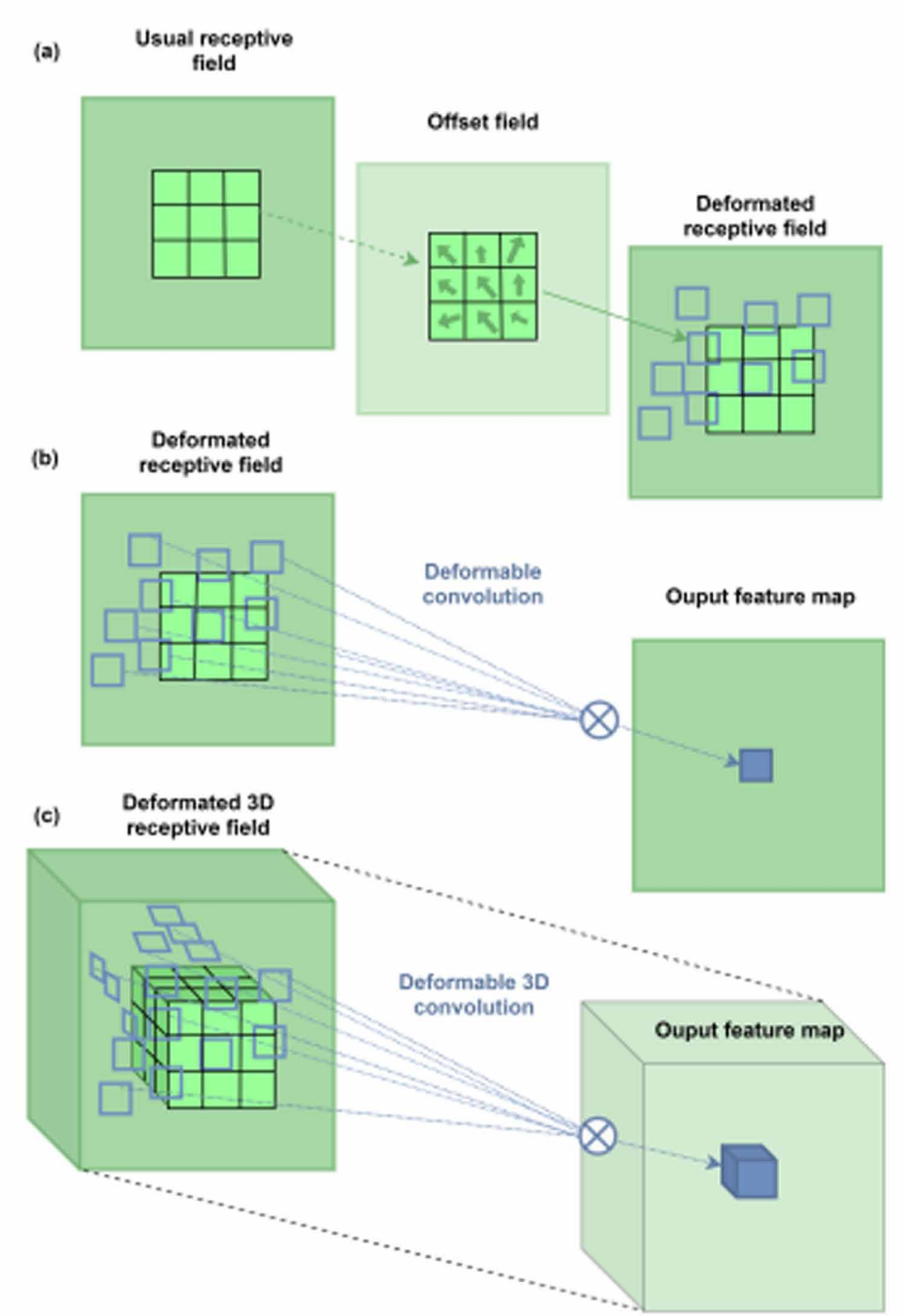
ii. Proposed Network

The architecture of proposed network is shown in Figure 8.

The architecture consists of a contracting path (encoding layer) to capture the context and a symmetric expanding path (decoding layer) for precise localization. In both encoding and decoding layer, the deformable convolutions are used. The segmented lung images of size 256×256 along with ground truths, are given as input to the first layer of contracting path which is first passed through normal convolutional block and then through deformable convolutional block. The normal convolutional block applies the fixed size sample matrix, which is added with the offset in the deformable block and provides irregular sample matrix on the input feature map. Then max-pooling operation is applied on this feature map and again same process is repeated. The feature maps are down-sampled by a factor of 2 in the encoded layer and again up-sampled by the same factor in decoding layer. Also feature maps from the layers in contracting path are concatenated with the corresponding layer in expanding path for precise localization. At the output, the predicted masks for tumors are obtained. The network is trained for 250 epochs, as after this overfitting starts. For optimization, Adam optimization is used. The learning rate is initialized at 0.0001 with a decay factor of 10^{-1}.

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Figure 6. An illustration of (a) 2D deformable convolution generated from 2D normal convolution (b) 2D deformable convolution and (c) 3D deformable convolution deformable convolution, Source: (Pominova, 2019)



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Figure 7. (a) Normal and (b) Deformable Convolution applied on a lung CT image

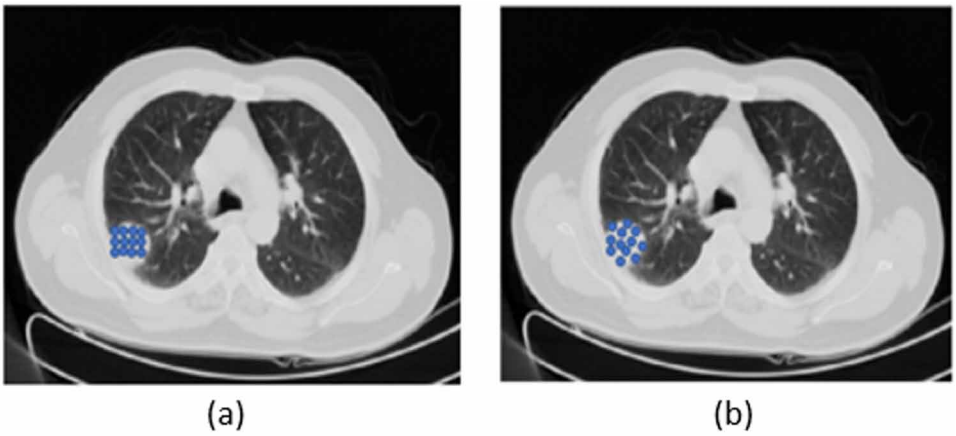
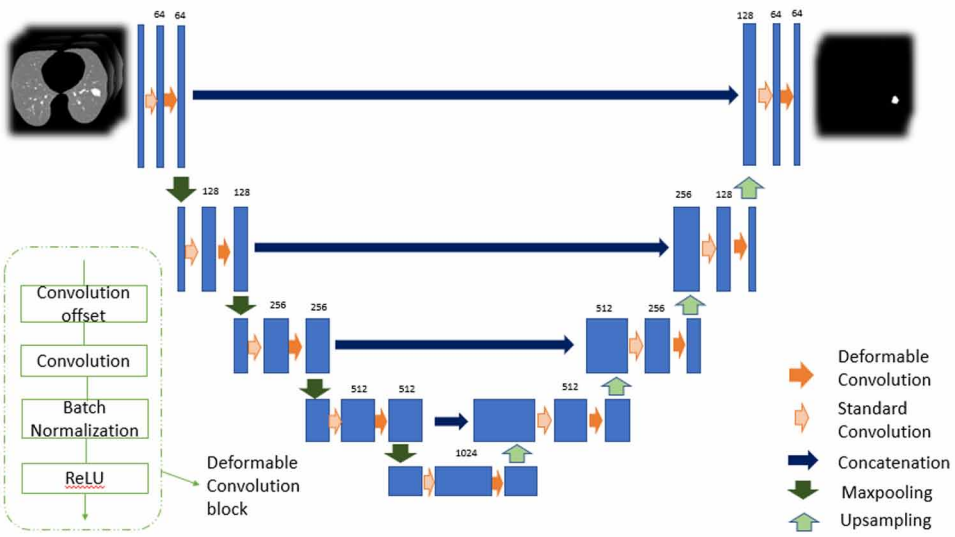


Figure 8. Architecture of proposed 3D CNN with deformable convolution



RESULTS AND DISCUSSION

For evaluation of the proposed method, the dice coefficient is used which is defined in equation (3). Dice coefficient is a measure of relative overlap and is used to compare between ground truth and predicted mask and it is a good measure for predicting the performance of image segmentation.

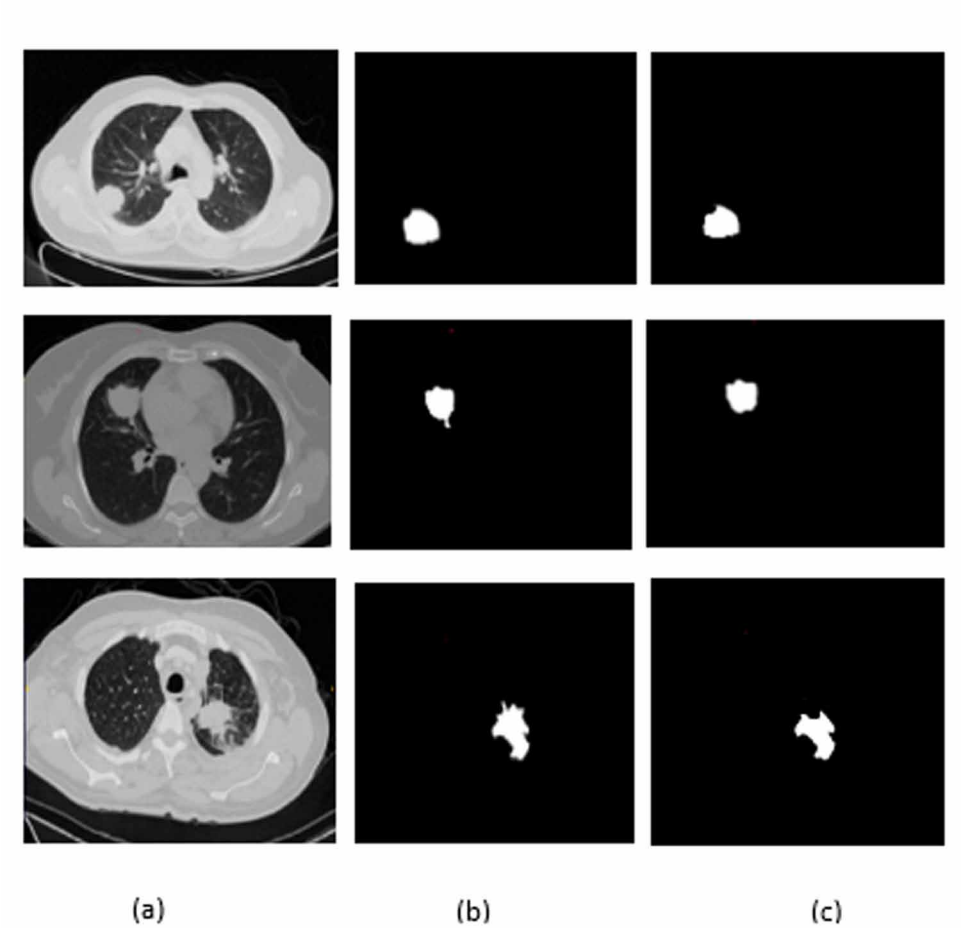
$$D = \frac{2\left(|A| \cap |B|\right)}{|A| + |B|} \tag{3}$$

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In equation (3) Dice coefficient (D) is defined, A is predicted mask and B is ground truth. The range of D is [0, 1] where 0 means false positive (no tumor but the algorithm is detecting false presence of tumor) and 1 means true negative (no tumor and the algorithm is correctly detecting its absence).

The network is trained on a total 472 CT scans combined from both the datasets used in this work. For training the authors have used 16 GB NVIDIA P100 GPU using cuDNN v5.0 and CUDA 8.0 with 128 GB RAM. For testing the network 80 CT scans are used and the dice coefficient of 77.23% is obtained, which is better than the previous methods. The comparison of proposed method with other methods is presented in Table 2. And the results are shown in Figure 9., which shows that the predicted masks are very close to the ground truth masks.

Figure 9. Comparision between ground truth and predicted mask from proposed method (a) CT image, (b) ground truth and (c) predicted mask



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Table 2. Comparison of performance with other methods

Model	Dice Coefficient
2D UNet	0.62
3D UNet	0.73
2D LungNet	0.67
3D LungNet	0.70
Recurrent 3D DenseUNet	0.75
Proposed Method	0.77

FUTURE RESEARCH DIRECTIONS

Deep learning is an emerging field and providing best solution in every industry including healthcare sector. The proposed work in this chapter is an attempt towards achieving the same goal for healthcare services. There are many scopes for future work in this direction like first, for lung segmentation, a deep learning algorithm can be utilized if ground truths are available, second a cascaded network can be implemented. The proposed network can be modified to get the higher evaluation score.

The advantage of 3D CNNs is that they can capture information from temporal as well as spatial dimension with the help of 3D convolutions and they learn the features by observing the consecutive slices in the 3D medical image. But the 3D CNNs are having some drawbacks as well like a 3D CNN consists of 3D convolutional layers which cause high computational cost and also high memory cost due to increased number of parameters and thus training a 3D CNN takes very long and requires high performance GPUs. To resolve this issue, cost efficient 3D CNNs should be designed, or a cascaded network consisting of both 2D and 3D CNNs can be used. Now a days GANs (Generative Adversarial Networks) are becoming popular in computer vision applications including medical image processing (Goodfellow, 2014). Some researchers have already used GANs for several medical applications like in (Pawar, 2021) for lung field segmentation and many more. So, GANs can also be used for lung tumor segmentation and its analysis. In this chapter, the authors have proposed a methodology for lung tumor segmentation but for the whole process of lung tumor analysis, there are more tasks included such as lung cancer stage classification, tumor growth analysis etc. which need to be performed to assist the doctor in determining a better treatment plan for the lung cancer patient.

CONCLUSION

In this chapter, the authors have proposed a 3D CNN with deformable convolutions for lung tumor segmentation. The proposed network is trained and tested on two different datasets, one collected from an Indian local hospital and another dataset named NSCLC-Radiomics, obtained from an online platform. The major aspect of the proposed network is that it uses the deformable convolutions which utilizes the learnable sample matrix to learn the image features more accurately. The proposed 3D CNN can also be utilized for other medical applications. The limitations of deep CNNs are data scarcity, variations and data imbalance problem present in different datasets. The authors have tried to overcome this issue by

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using two different datasets, which differ in terms of image acquisition device, slice thickness, image quality etc. The network trained on these different datasets generalize well on new unseen data.

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Chapter 2
An Intelligent Approach for Prediction of Life Style Conditions in Adolescent Girls by Analyzing Health Parameters

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ABSTRACT

Monitoring health parameters has become a challenging task due to unpredictable diseases and related symptoms. Lifestyle is a crucial factor to decide to be healthy, in adolescent girls especially. This chapter presents a work in progress on prediction of lifestyle of adolescent girls based on problems like unhealthy routines of eating habits, sleep patterns, stress, etc. Therefore, an IT-enabled system is presented to assess current lifestyle of adolescent girls in an easy and faster way. A systematic survey is conducted with specially designed survey form by consulting medical practitioners and physical trainers. Twenty-one factors related to age, diet habits, exercise habits, sleeping habits, health history, etc. are included in the expert-guided form. One hundred fifty-five individual responses are collected and assessed manually by medical experts to annotate as healthy or unhealthy types. The healthy lifestyle prediction accuracy with support vector machine is 83.87% whereas it is 80.64% using logistic regression.

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1. INTRODUCTION

Lifestyle diseases are caused by few routine behavioural factors: diet habits, sleeping habits, lack of physical activity, level of stress, alcohol intake etc. Majority lifestyle diseases are chronic in nature, commonly termed as non-communicable disease (NCD) (Tabish, 2017). As per World Health Organization (WHO) factsheet on NCD, around 70% of deaths across the world are caused due to unhealthy lifestyle choices (WHO, 2017). Millions of teenage follow an unhealthy lifestyle due to wide changes occurred in the way of living life. Poor lifestyle choices include unhealthy diet, irregular sleeping patterns, overconsumption of alcohol, regular smoking, drug addictions, lack of exercise, wrong body postures, insufficient release of stress, malnutrition, etc. And such lifestyle choices lead towards progression of chronic non-communicable diseases including diabetes, heart disease, high blood pressure, cancer, obesity, migraine, depression, chronic back pain, hormonal imbalances etc. Unfortunately, these choices have become the dominant lifestyle in current generation children and teenage girls which may have long-term impact on women's health as per the seven-month long survey conducted by gynaecologist in Navi Mumbai, India (India Today Web Desk, 2018).

In life style, the significant health problems in children, adolescents and adults occur due to overweight and obesity. One of the reasons for premature death risk or some disabilities in adult age is obesity. The problems like obesity and overweight may be the prominent cause of the health disorder risk. According to research studies, there is increase in the occurrence of adolescents, overweight and obesity in most of the countries. It is been observed that above 30% of all children, are obese. In adolescent's healthy intake is mostly due to the awareness and evaluation of eating habits which are considered to be healthy. In children several diseases are found which includes cardiovascular disease, psychological problems, breathing complications, increased risk of fractures, hypertension etc (C3 Collaborating for Health, 2011). Dieting habit encompasses strategies to promote the health with increase in chances of problems related to health. As per survey data, it is revealed that women and adolescent girls are focussed to weight control with dieting. The dietary guidelines should be followed promoting good health. Meal skipping may leads to several health problems like energy imbalance and eating disorders in children and adolescent girls (WHO, 2017). The research documents discuss adolescents have problems in understanding as well as in practicing healthy eating behaviours. There is limited understanding of healthy eating options and better understanding of unhealthy eating among the early adolescent girls. Several international studies come up with the facts that adolescent people's diet usually does not survive to health recommendations at National level (India Today Web Desk, 2018).

In recent decades, "Lifestyle Management for Teenage" has become a challenge for parents, medical practitioners and a point of attention for researchers. Therefore, it is required to attend this issue at most priority, which is responsible for our health condition as well as our immune system. And such issue can be solved with an automated artificial intelligence-based system, which can help to assess lifestyle of teenage girls and help to alarm for their unhealthy conditions and its impact. In this regard, the machine learning based models can assist in designing smart healthcare solutions for lifestyle management and for prevention of lifestyle disease conditions.

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2. RELATED WORK

Good healthful behaviour leads to good lifestyle. In contrast, bad behaviour habits lead towards lifestyle diseases. According to the existing studies, there are varying lifestyle patterns and different forms of significant influences. Our discussion is hereby categorized based on different variables of lifestyle that are key contributors for impact on health.

Diet is a very important factor for defining the healthy or unhealthy lifestyle. Diet habits of people changed substantially from the mid of 20th century across the world, especially in developing and developed countries. The changed diet habits include the increasing intake of non-veg, dairy products, vegetable oils, alcoholic beverages, harmful drinks with lots of sugar contents (Key et al., 2002). Most of these foods are tasty to be easily loved by teenage but these have bad fats, high amount of calorie, carbohydrate and salt. Poor diet is the common problem majorly in urban area and it can be assessed with the measurement like body mass index (BMI), etc (Farhud, 2015). Urban environment primes towards the consumption of fast food. Even variety of junk food, street food is available at any time during day or late-night timings and these are becoming as a daily habit among teenage group. These food intake habits are increasing the problems like obesity, cardiovascular disease, diabetes (Mozaffarian et al., 2011). There is a rise in overweight problems among teenage and young people. Around 19% teenage girls are surveyed as overweight or obese in urban south India (Michael et al., 2018).

Another important lifestyle attribute is sleep. Sleep plays a vital role in maintaining health and it matters a lot in the teenage population group. Biologically sleep pattern varies within the age range of 12-22 years. But there are also external factors like social, academic, environmental, which is affecting the sleep patterns in adolescents and these factors have become the necessary part of modern way of living life (Graham, 2000). Nowadays, it is observed an increased impact of technology on sleeping habits (sleep timing, duration and quality) of teenage. The excess use of mobiles, TV, laptops or other electronic gadgets is being observed among teenage population. The addiction of playing games, watching entertainment related videos, socializing with friends etc cause for the delayed sleep timings and its further impact on daytime sleepiness, energy less feeling (Keyes et al., 2015; Matricciani et al., 2012). Insufficient sleep exerts adverse effects on body like risk of obesity, chronic diseases, hormonal changes (Bruce et al., 2017; Cappuccio et al., 2008; Chaput et al., 2015; Chaput & Tremblay, 2012). Also, spending excess time regularly with electronic gadgets cause for neck pain, back pain, even glaucoma problem (Sharma & Majumdar, 2009).

Lack of physical activity is also one of the main reasons for causing lifestyle diseases. Routine exercise along with healthy diet help to improve and maintain the well-being (C3 Collaborating for Health, 2011; Dunn et al., 1998). Tobacco, alcohol intake, drugs become a major threat to public health, which are leading cause for depression and further impact for chronic conditions (Cabello et al., 2017). Around 3-7 million deaths are estimated per year globally because of tobacco, alcohol, physical inactivity and obesity (Majid, 2018). One more major factor gaining research attention in recent years is stress among teenage girls. Unmanageable stress contributes towards changes in eating habits, sleeping patterns, temptation for alcohol or drug intake, smoking. There is an association discovered between stress and diseases like obesity, metabolic changes, migraine headaches, hypertension, cardiovascular problems (Yau & Potenza, 2013).

As can be seen from above discussion and few statistics based on surveys, all above mentioned risk factors are human-behaviour driven. These can be dealt at individual and social level by making modifications in lifestyle. Healthy diet, regular exercise, proper quality sleep, cessation of smoking

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or drinking, maintaining weight help to reduce the risk of various influences of unhealthy lifestyle on human health. Such preventive measures or corrective remedies help to diminish the mortality rate of non-communicable diseases (Sharma & Majumdar, 2009).

Nowadays, IT based healthcare management and analysis methods are greatly succeeding with the help of machine learning algorithms. Few machine-learning based studies have conducted critical analysis of routine behavioural data and health parameters for initial lifestyle-based disease diagnosis. Different techniques like support vector machine, random forest, naïve bays, neural network, K-nearest neighbour, decision tree, adaboost, bagging, etc. are used for automated lifestyle related analysis (Razzaghi et al., 2016; Sharma et al., 2018).

An effective use of machine learning based model can benefit in developing smart healthcare solutions for lifestyle management and for prevention of lifestyle disease conditions. The research work by (Agarwal et al., 2016) experimented hybrid approach for well-being prediction which involves the combined predictive analysis using machine learning methods and expert's assessment. Among the multiple methods, which are experimented using nine machine learning supervised classifiers, random forest outperformed with area under curve (AUC) of 0.726 (Agarwal et al., 2016). In the study by Patil et al, support vector machine-based model performed well with an accuracy of 92.3% for lifestyle disease prediction. It yielded the binary results to classify the well-being status using ratings on 1-5 scale for patient attributes like unhealthy eating habits, obesity, anxiety, poor sleep, physical inactivity, smoking, alcoholism combined with demographic details like age, gender of patient (Patil et al., 2018). It is surveyed that Support vector machines (SVM) as the most effective and commonly used algorithm for diabetes prediction based on lifestyle, physical activity, eating habits (Brisimi et al., 2018; Kavakiotis et al., 2017). Other models also evaluated the association of wellness parameters and occurrence of diabetes using Bayesian network and multilayer perceptron (Behara et al., 2014). Few diagnosis models are proposed for cardiovascular disease prediction using random forest, naïve bays, support vector machine (Dinesh et al., 2018). A hybrid model of bayesian network is developed to visualize the trend of lifestyle diseases in focused cohort group (Ilham, 2017).

Very few models are available with existing studies working on deep learning techniques for lifestyle-based health status and disease prediction. Most recent lifestyle habits available in Korea National Health and Nutrition Examination Survey (KNHANES) dataset, having 760 variables and around 22,00 cases, are analysed using recurrent neural network to predict chronic diseases like hypertension, stroke, diabetes, cardiovascular problems (Kim et al., 2019). The risk factors of arthritis were assessed using deep neural network and principal component analysis (Lim et al., 2019). The work by Lim et al. demonstrated the health status as one of the top performing features with the correlation coefficient value of 0.215, which includes lifestyle related variable like smoking status, body mass index, obesity, alcohol intake, self-reported status of health, physical activity, and medically diagnosed chronic disease. The impact of bad lifestyle habits leads towards the disease like diabetes, heart problems, cancer etc. AI based models with existing literature (Jackins et al., 2021) yielded an accuracy of 74.4%, 82.3% and 63.7% using Bayesian classifier and showed the accuracy values of 74%, 83.8% and 92.4% with random forest classifier. The lifestyle related diseases are predicted with results of precision and recall values 0.32 and 0.89 by analysing health check-up data using decision tree classifier (Tsunekawa et al., 2019).

Adoption of healthy lifestyle in daily routine of adolescent girls helps to prevent the possibility of lifestyle diseases. In addition, machine learning can definitely help to identify the preventable risk factors by analysing the health parameters of teenage girls. Such analysis will certainly assist to decide the changes to be adopted in routine behaviour. This will improve the overall health of adolescent girls and

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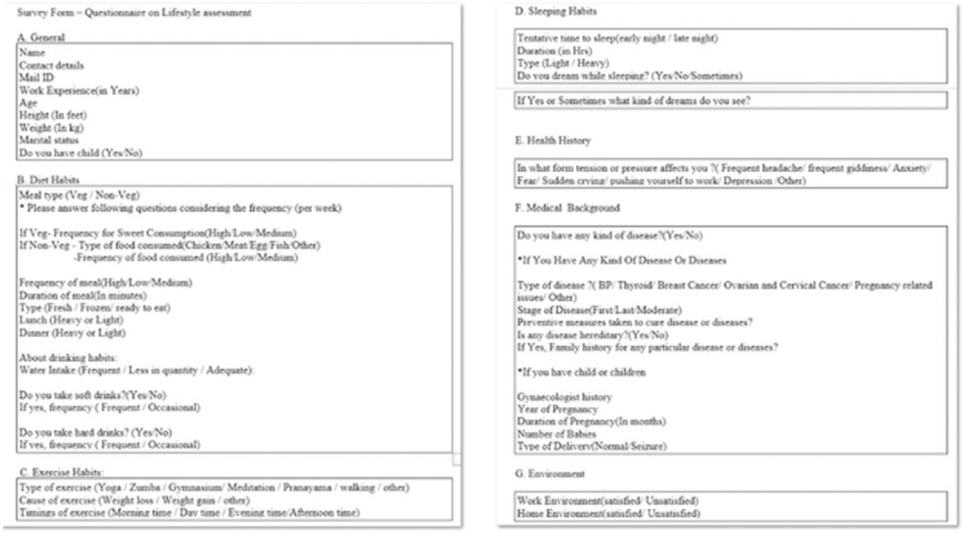
in turn, future women population. Such intelligent system will provide initial level diagnosis to assess the current lifestyle status with reduced time. Other benefits are also there in terms of reduced medical costs which may be needed to put for variety of screening test like smoking screening test, alcohol screening test, obesity test etc. Therefore, the aim of our study is to analyse the routine behaviour and health parameters in order to predict the risk of lifestyle conditions, which are surveyed among adolescent girls in Pune region of Maharashtra, India.

3. BACKGROUND: DATASET CREATION FOR PROPOSED WORK

The data sample collection is most important for the proposed work. A survey form was designed and data is collected in February 2020. Several college girls of adolescent age were participated by filling the survey forms. These questionnaires are prepared in discussion with medical practitioner and certified yoga therapists. All the self-administered 300 questionnaires are distributed to 200 girls. These samples and related research process is confined to Pune region.

A survey form contains simple questionnaire about lifestyle habits. The Information is all about age, weight, duration or timings of meal, meal type, type of food consumed (veg, non-veg), type of lunch, type of dinner, frequency of sweet consumption, hard drink habits, soft drink habits, timing of exercise, type of exercise, cause of doing exercise, type of food consumed, frequency of sweet consumption. Some of these are discussed here taking reference from published articles. Figure 1 represents the sample survey form.

Figure 1. Survey Form


Survey Form – Questionnaire on Lifestyle assessment

A. General

Name
Contact details
Mail ID
Work Experience(in Years)
Age
Height (In feet)
Weight (In kg)
Marital status
Do you have child (Yes/No)

B. Diet Habits

Meal type (Veg / Non-Veg)
* Please answer following questions considering the frequency (per week)

If Veg- Frequency for Sweet Consumption(High/Low/Medium)
If Non-Veg - Type of food consumed(Chicken/Meat/Egg/Fish/Other)
-Frequency of food consumed (High/Low/Medium)

Frequency of meal(High/Low/Medium)
Duration of meal(In minutes)
Type (Fresh / Frozen/ ready to eat)
Lunch (Heavy or Light)
Dinner (Heavy or Light)

About drinking habits:
Water Intake (Frequent / Less in quantity / Adequate):

Do you take soft drinks?(Yes/No)
If yes, frequency (Frequent / Occasional)

Do you take hard drinks? (Yes/No)
If yes, frequency (Frequent / Occasional)

C. Exercise Habits:

Type of exercise (Yoga / Zumba / Gymnasium/ Meditation / Pranayama / walking / other)
Cause of exercise (Weight loss / Weight gain / other)
Timings of exercise (Morning time / Day time / Evening time/Afternoon time)

D. Sleeping Habits

Tentative time to sleep(early night / late night)
Duration (in Hrs)
Type (Light / Heavy)
Do you dream while sleeping? (Yes/No/Sometimes)

If Yes or Sometimes what kind of dreams do you see?

E. Health History

In what form tension or pressure affects you ?(Frequent headache/ frequent giddiness/ Anxiety/ Fear/ Sudden crying/ pushing yourself to work/ Depression /Other)

F. Medical Background

Do you have any kind of disease?(Yes/No)

*If You Have Any Kind Of Disease Or Diseases

Type of disease ?(BP/ Thyroid/ Breast Cancer/ Ovarian and Cervical Cancer/ Pregnancy related issues/ Other)
Stage of Disease(First/Last/Moderate)
Preventive measures taken to cure disease or diseases?
Is any disease hereditary?(Yes/No)
If Yes, Family history for any particular disease or diseases?

*If you have child or children

Gynaecologist history
Year of Pregnancy
Duration of Pregnancy(In months)
Number of Babies
Type of Delivery(Normal/Seizure)

G. Environment

Work Environment(satisfied/ Unsatisfied)
Home Environment(satisfied/ Unsatisfied)

1. Meal Type: Girls were asked about the type of meal they have. It is classified into vegetarian (veg) and non-vegetarian (non-veg). Research studies about meal type and its impact discuss that **non**-vegetarians are found to be learner compared to vegetarians. The health parameters like control of blood pressure, body mass index, low cholesterol etc are found to be good in vegetarian. **Vegetarian**

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diet makes us capable to maintain weight in a long run. People eat non-veg like Chicken, Meat, Egg, Fish. It shows that 52.9% people eat Chicken.

2. Frequency for sweet Consumption: It is classified into high, medium and low. According to the World Health Organization, the recommendations of daily sugar intake are dropped from 10 percent to 5 percent. An adult with normal body mass index (BMI), can have 25 grams of **sugar** daily. Dataset shows that 13.6% people have high consumption of sweet, 62.1% prefer medium and 24.2% prefer low sweet consumption.
3. Consumption of type of Non-Veg food: They were classified into chicken, meat, egg, and Fish. Non-veg food is good for human beings. For example, the proteins you get from veg food sources are incomplete but Overconsumption of red meat is not good for health as it contains saturated fats that lead to heart disease.
4. Duration of meal: The respondent has to describe the time in minutes.
5. Type of Meal: Classification is done based on Frozen, Fresh, Ready to eat or Stale. Dataset have 74.8% people who eat fresh food and 12.4% people who eat Ready to eat food.
6. Meal type shows type of meal taken by people i.e veg or non-veg. It shows that 51.6% people prefer non-vegetarian food and 48.4% people eat veg.
7. Type of lunch: Heavy or Light. Heavy breakfast is mostly not preferred. Even though breakfast is not skipped, it is found that long waiting for heavy lunch may be beneficial. Ne calories till 3 pm can lose their weight than the people who don't eat till 3 pm. This study published in 2013 in International Journal of Obesity. As per dataset, 67.3% people eat heavy lunch and 32.3% people eat light lunch.
8. Type of Dinner: This classified into heavy and light. Mostly people lose their weight by making largest meal as breakfast. This study was published in January 1997 in the Journal of Nutrition. It is found that for maintaining easier time for muscle mass with dieting, making dinner as largest meal is beneficial. It helps to lose weight and fat muscle. Fig 14. Type of Dinner in dataset shows that 63.2% people have light dinner and 36.8% people have heavy dinner.
9. Water intake: It was classified into frequent, less in quantity, or adequate. The National Academies of Sciences, Engineering, and Medicine state that one should have daily an adequate fluid intake. This can be about 2.7 litre water or any fluids intake for women daily.
10. Soft drink Consumption: Yes or No.
11. Hard drinks Consumption: Yes or No.
12. Frequency of taking hard drinks: Classified on a point scale of frequently or occasionally.
13. Type of Exercise: Exercises were classified into different types like zoga, zumba, meditation, pranayama, Gymnasium, walking.
14. Cause of doing the exercise: weather it is for weight loss or for weight gain.
15. Timing of exercise: It is classified as Morning, Evening, or Night. The Journal of Physiology study found that exercising between 1 p.m. and 4 p.m. can shift forward your body clock in the same way as an early morning workout. Even taking a quick walk may help you perk up and refocus. Survey shows that 62.6% people exercise in morning, 12.3% at night, 22.6% in evening and 2.5% people in afternoon.
16. Bedtime: It is classified as early night or late night.
17. Duration of sleep: It is classified in a time scale of 1 to10. Tentative time to sleep is sleeping habits of people. It shows 61.3% people choose to sleep late night while 38.7% people sleep early night.

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18. Type of sleep: It is classified as Heavy or Light. The Sleeping habits recommended by WHO for the age 18 to 25 years is 7 to 9 hours. Survey shows 59.4%people take heavy sleep while 40.6% people take light sleep.
19. In what form tension or pressure affects them: They were classified into Frequent headaches, frequent giddiness, anxiety, fear, sudden crying, depression, and pushing themselves to work.

4. RESULTS AND DISCUSSION

This section discusses the result and analysis of health parameters, collected through the survey reports. The performance parameters like accuracy, precision, recall to evaluate the results of classifiers are discussed. The classification of data samples with various classifiers results into categorization as healthy or unhealthy parameters. The detail discussions are given in following sub sections.

4.1 Performance Measures

The performance of classifiers is evaluated with the accuracy as a performance measure. The confusion matrix calculates true positive (TP), false positive (FP), true negative (TN) and false negative (FN) values. The four metrics; accuracy, precision, recall, and F1-score are as presented in equations 1-4 (Key et al., 2002). Here, TP is how correct the value is predicted as needed and it indicates for healthy lifestyle prediction. FP is how incorrect the value is predicted as needed and it shows healthy lifestyle prediction for unhealthy lifestyle. TN is how correct the value is predicted and not needed. FN is how incorrect the value is predicted as needed and it shows unhealthy lifestyle prediction for healthy lifestyle.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}. \tag{1}$$

$$Precision = \frac{TP}{TP + FP}. \tag{2}$$

$$Recall = \frac{TP}{TP + FN}. \tag{3}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}. \tag{4}$$

4.2 Discussion: Analytical Observations

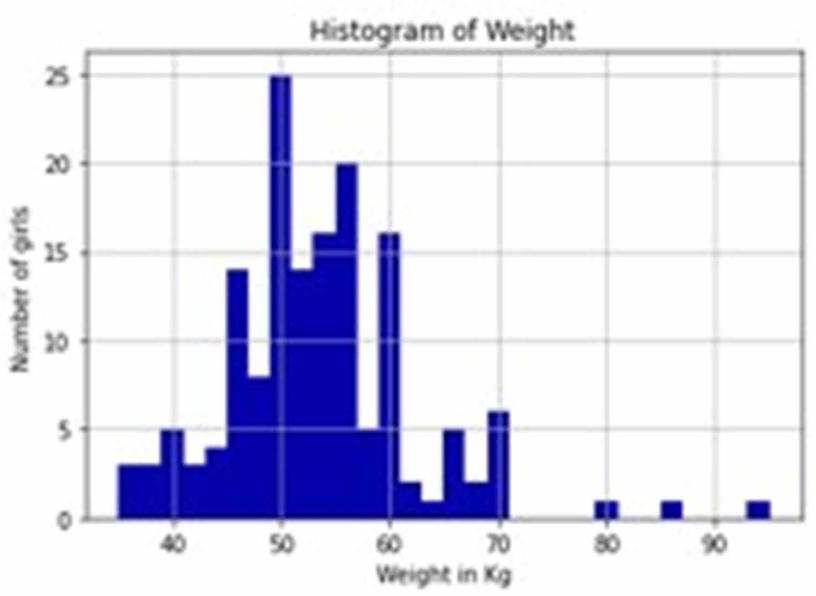
The data of health parameters which are defined in discussion with the medical practitioners and yoga therapist are collected through surveys are analysed and results are discussed. These parameters contribute in determining health type as healthy or unhealthy. These results are further compared with the results of machine learning classifiers. The parameters are confined to routine diet, eating habits, drink-

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ing habits etc. which are categorized on age and weight. This analysis is discussed with the experts for their opinion. The results are presented next.

1. Average weight is around 53 kg and average height is about 157 cm. The body mass index is around 21.50 with the specified average weight and height. As per standards, BMI with value of 21.50 is an indicator of good health. But this BMI is observed for the samples ranging from 35 to 95 kg weight for which BMI ranges from 14 to 38. It indicates the underweight and overweight as well as obese cases. The below figure 2 shows the histogram of weight of all samples.

Figure 2. histogram of weight of all samples



2. There is strong association between sweets in food intake and weight. The frequent consumption of sweet items relates highly with average weight, which is around 55% for total 17 girls. However, the average weight is less than 50% for 82 girls taking less sweet intake as shown in figure 3.
3. It is surprised to know that the average duration of taking meals is about 44 minutes among these adolescent girls. The reasons maybe due to getting engaged with other tasks like watching TV, playing with mobiles, talking, etc while taking meal and giving it less importance. But around 48% girls are observed finishing their meals within 20-30 minutes.
4. Around 36% girls are taking heavy meal at night. Even taking meal at night have significant impact on increase in weight as observed in following figure. Average weight of 57 girls taking heavy dinner is about 56 kg whereas it is about 52 kg for total 98 girls taking light dinner. And this is on higher side as compared to average weight of girls taking heavy meal in the afternoon and light dinner as shown in following figure 4.

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Figure 3. Sweet Consumption Vs Average Weight

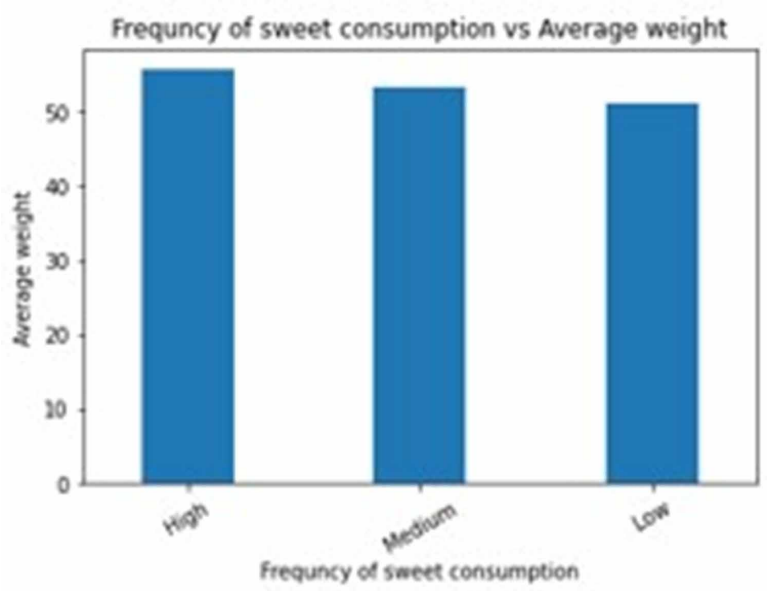
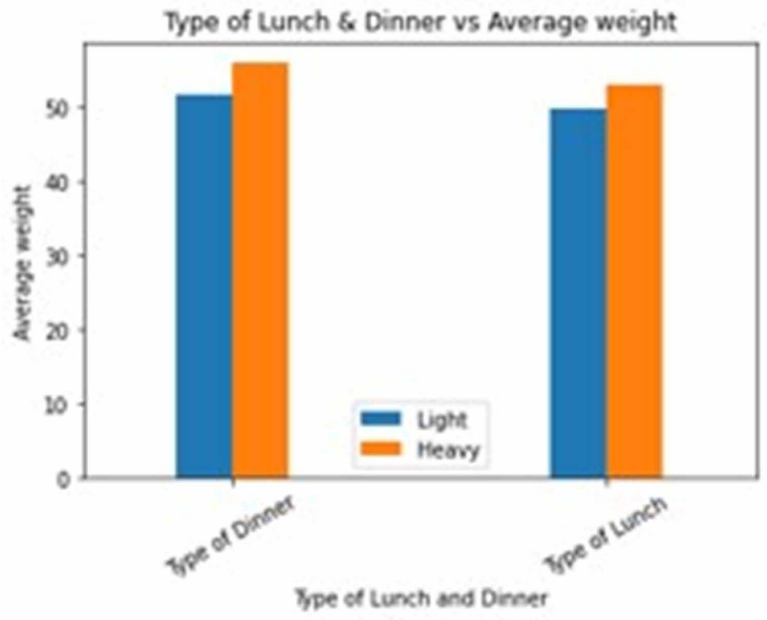


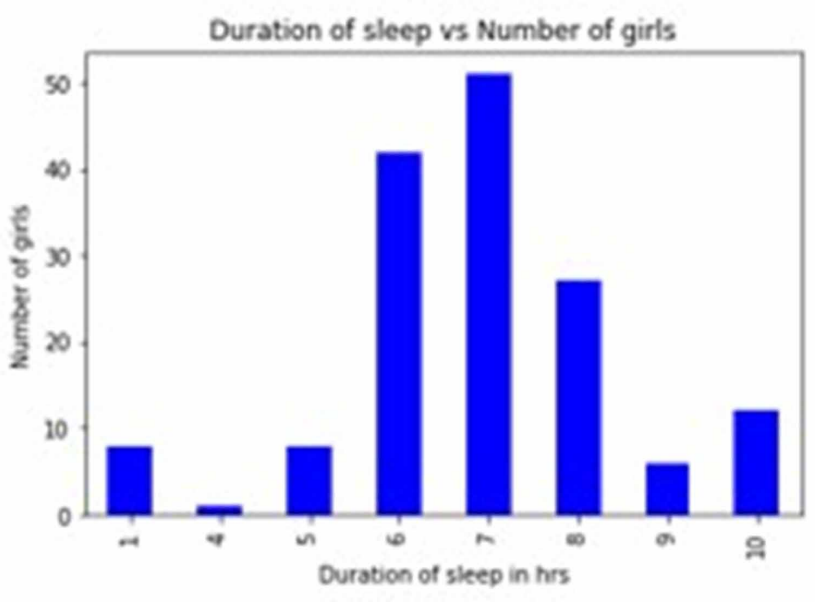
Figure 4. Type of Lunch and Dinner Vs Average Weight



5. The average sleep timing of all samples is about 6 hrs 40 minutes. About 76% girls take adequate sleep for 6-8 hrs. The sleep pattern for remaining 24% girls is alarming from health point view, which includes the sleeping duration with the values of 1 hr, 4 hrs, 5 hrs, 9 hrs and 10 hrs as shown in figure 5. About 30% girls are not drinking water adequately, which is not good for health.

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Figure 5. Duration of sleep Vs number of girls



4.3 Machine Learning Classifiers for Prediction of Healthy or Unhealthy Life Style

Machine learning algorithms are powerful in extracting interesting features from the data. In this work several machine learning algorithms are tested to classify the features extracted from survey statistics and further to predict the lifestyle as healthy or unhealthy. Support Vector Machine and Regression Analysis are selected for the prediction of healthy and unhealthy lifestyle. Table 1 depicts results with SVM classifier with 80:20 train-test split. The accuracy is 84%. Table 2 depicts results with Logistic Regression with 80:20 train-test split. The accuracy is 81%.

Table 1. Life style prediction with SVM

Class	Precision	Recall
Class with label '0' (Healthy)	0.95	0.82
Class with label '1' (Unhealthy)	0.67	0.89
	Accuracy 83.87% and f1-score is 0.88	

Table 2. Life style prediction with Logistic Regression

Class	precision	recall
Class with label '0' (Healthy)	0.94	0.77
Class with label '1' (Unhealthy)	0.62	0.89
	Accuracy 80.64% and f1-score is 0.84	

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Figure 6 represents the confusion matrix of results obtained using support vector machine and figure 7 presents the confusion matrix of results obtained using logistic regression.

Figure 6. Confusion matrix of Support Vector Machine

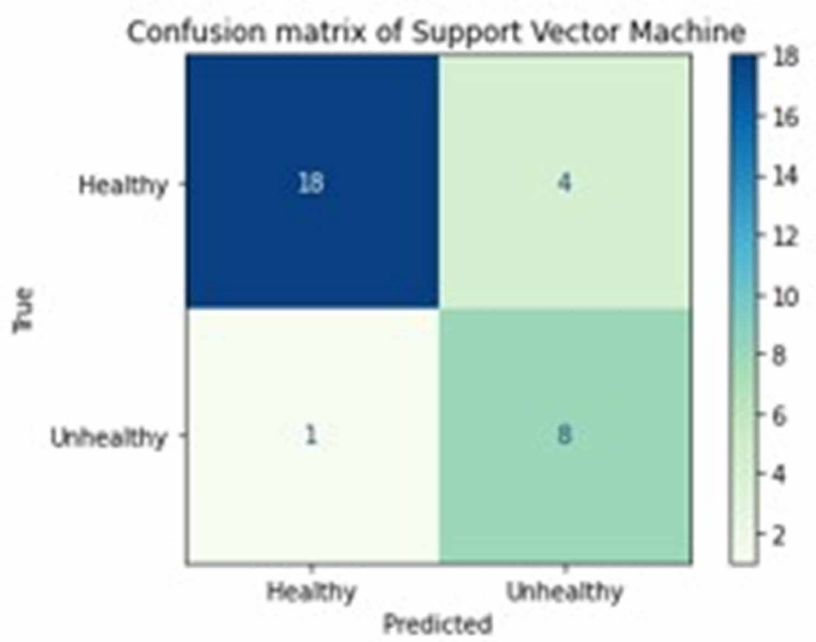
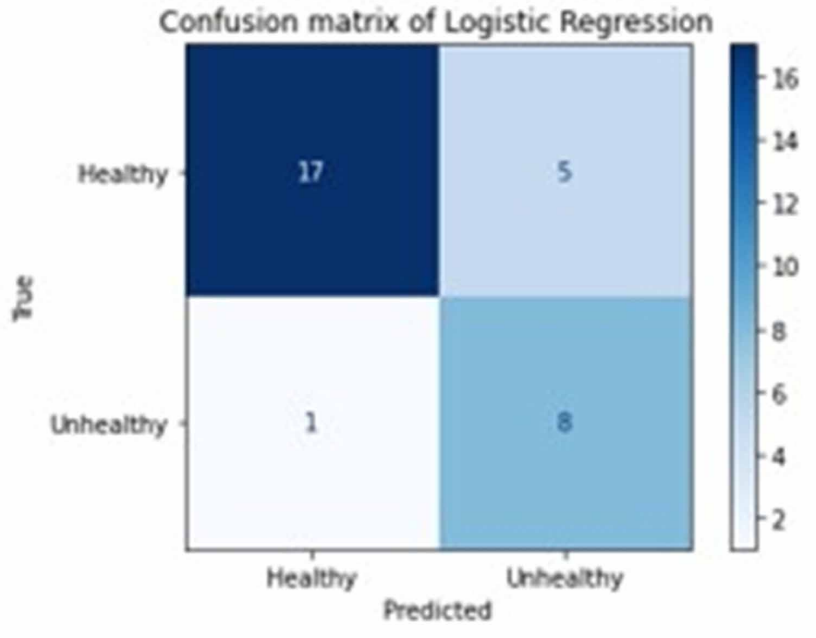


Figure 7. Confusion matrix of Logistic Regression



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5. CONCLUSION

Adolescence is the most important period of human life. It is the transition period from childhood to adulthood. During this period several changes take place in the body of adolescent girls. Health and nutritional status of an individual throughout adolescence is defined mostly by growth assessment. In this research the health parameters of adolescence are analyzed, and further evaluated with machine learning algorithms for the prediction of life style. The healthy life style prediction accuracy with Support Vector Machine is 83.87% whereas for Logistic regression it is 80.64%.

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Chapter 3
Anxiety Detection Using Physiological Data and Wearable IoT Devices: A Survey

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ABSTRACT

Anxiety has been the primary cause of multiple illnesses in society. Gadgets, smartwatches, and wristbands have become an integral part of our daily lives and are widely used. This shows whether wearable sensors and technologies can be used to prevent anxiety and stress. The authors look at recent research on recognizing anxiety in everyday life in this chapter. There are few studies that examine the detection of stress in daily life, as there are few studies that examine a variety of tasks involving the recognition of anxiety in regulated laboratory settings. In this analysis, the authors isolate and examine tasks based on the physiological modality used and their intended areas, such as the workplace, education, automobiles, and the uncontrolled conditions of everyday life. In addition, they explore promising technologies, prevention, and research issues.

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INTRODUCTION

Over the past few decades, investigators have observed that there exists an important link between a person's physical and emotional conditions (Hung & Picard, 2016). There has been increased interest in Affective Computing (AC) using technology to recognize a person's affective state. The first book on affective computations was from the Massachusetts Institute of Technology (MIT), Dr. Was written by A. Pentel et. al (Pentel, 2018). Considering then it has become an important chapter of the field of contact between humans and machines (Picard, 2003), (Picard, 1999). It uses a person's mental and behavioral gestures to measure current sentiments. The primary emotional statements in affective computation can be contained by excitement, anger, frustration, resentment, grief, and fear (Hung & Picard, 2016). The above feelings have recently been associated with anxiety. It can be defined as a response to demands and expectations that does not match your skills and knowledge and which can challenge your handling skills (WHO, n.d.). In contemporary culture, depression is a major concern. It is a growing problem and an essential part of our everyday lives. Early detection reduces damage and prevents it from getting old. Researchers have recognized harmful effects of anxiety on human health and recently lots of work has been done on the development of automated anxiety measurement systems using advanced AC algorithms and smart devices. Potential areas of use of automated stress detection systems can be identified in the vehicle environment such as driver stress checking, passenger stress detection and commercial flight relief in aircraft, especially in case of flight phobias, for workplaces (in factories and offices evaluation of stress for workers), evaluation of patients' stress rate and continuous tracking of candidates to assist counselors in work interviews and video consultations.

In this area, there are some surveys. in (Sioni & Chittaro, 2015), without reference to the related research and papers, the authors describe the types of physiological signals. They exposed only the types and characteristics of physical signals. Thapliyal et al. (Thapliyal et al., 2017) have introduced such stress detection devices in the market. A brief literature review Greene et al. (Greene et al., 2016) each type of beacon is given for physiological signals and widely used devices. Also presented in a very small survey, Gulhane et al. (Gulhane & Ladhake, 2019) reported several literary techniques. The downside of these works is that they did not provide literature using these technologies, although they did clarify the expansion of these technologies and off-shell products. The lack of literature on smartphones, digital devices, and smart bands is an important aspect of these articles. In (Carneiro et al., 2019), (Alberdi et al., 2016), the authors identified occupational anxiety detector studies. Nevertheless, the recent trend of anxiety recognition research is to consider stress not only at work but also in people's everyday lives. Our paper explores the following noteworthy novel parts of anxiety identification research:

- The kinds of gadgets and ordinarily extricated highlights were talked about for each physiological signal.
- Our ultimate objective of anxiety detection studies is to relieve a person from anxiety after detection.
- Our objective is to identify the research directions and problems encountered in open research in the matter of stress detection.
- We are also making comparisons between existing anxiety detection techniques.

In this study, in Section 2 and Section 3 we first describe and characterize the symptoms of anxiety. The methods of anxiety induction in section 4 are also described briefly. Section 5 provides physiologi-

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cal signals for anxiety analysis, frequently used data collection methods, and features typically used for each signal. in section 6, we discuss the works about literature in a number of environments: on the road, vehicles, and in unregulated everyday circumstances. Section 7 briefly discusses the stress detection methods summarizing the literature. We end with the analytical challenges for the study of stress identification in section 8.

WHAT IS ANXIETY?

Anxiety is a broadly utilized term yet it is difficult to concur on a definition since it is emotional and hard to characterize the marvel (American Institute of Stress, 2006). In any case, if researchers can't characterize anxiety, how might they evaluate it? Merriam Webster's information reference characterizes anxiety as a physical, compound, or passionate factor that causes substantial or mental anxiety and might be a factor in malady causation. Up to a specific level, anxiety may be additionally useful in situations, for example, an interview for work, examinations in school. As mentioned earlier, anxiety is a system of the body that helps in basic matters and spares us. But once you are beyond a certain level, anxiety is not beneficial in any way, despite the expectation that it can begin to harm a person's well-being, passionate state, profitability, and living nature. The explanation is that our sensory system cannot separate between passionate and physical hazards (European Agency for Safety and Health at Work (EU-OSHA), 2014).

ANXIETY IMPACT ON SOCIETY AND ECONOMY

Anxiety has become a huge issue for present-day society. Workplaces among different spots added to the high pressure most (Alberdi et al., 2016). The confusion between work requests and capacities, time weight, and high outstanding tasks at hand are general purposes behind the workplace anxiety. Family-related issues, ailments, and ceaseless wounds and enthusiastic issues can be recorded as off-the-work environmental anxiety causes. Anxiety is the second most serious business-related medical problem in Europe (European Agency for Safety and Health at Work (EU-OSHA), 2014), after musculoskeletal sicknesses which can be brought about by anxiety sometimes (Colligan & Higgins, 2014). The American Institute of Stress uncovers that the US spends through 300 billion USD every year to illnesses brought about by anxiety (WHO, n.d.). In 2013, business-related pressure cost 25 billion euros to EU organizations (EU-OSHA, 2014). An ongoing open overview (Sedlatschek, 2014) uncovered that 51% of European laborers converse with anxiety at work environments. It is foreseen that 50–60% of all lost working days in the European business division brought about by business-related anxiety and psychosocial hazards (Alberdi et al., 2016).

STRESS INDUCTION TESTS

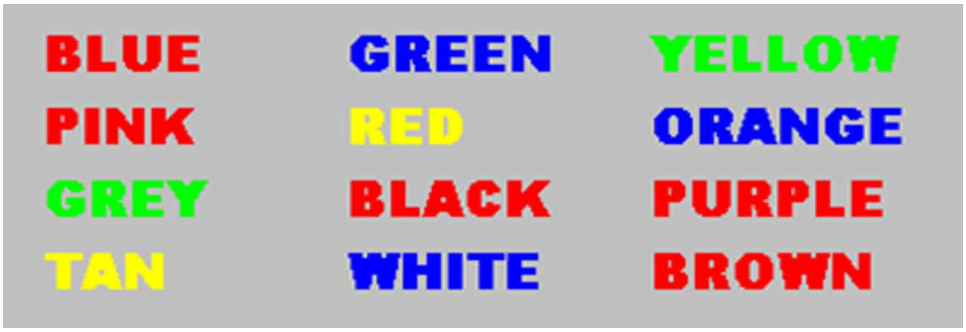
To examine anxiety in research center situations, subjects are approached to play out specific errands so as to actuate anxiety. In this section, the most conspicuous tests applied in the research facility conditions will be quickly portrayed.

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Stroop Color-Word Test

The Stroop Color-Word Test (SCWT; Stroop, 1935) is one of the most established and most broadly applied pressure acceptance tests (Scarpina & Tagini, 2017). A fundamental undertaking that exhibits this impact happens when there is a befuddle between the name of shading (e.g., "blue", "green", or "red") and the shading it is imprinted on (i.e., "red" imprinted in blue ink rather than red ink). When solicited to name the shading from the word it takes longer and is increasingly inclined to blunders when the shade of the ink doesn't coordinate the name of the shading. A case of the SCWT test is appeared in Fig. 1.

Figure 1. SCWT Test Example (Dedovic et al., 2005)



Montreal Imaging Stress Task

The Montreal Imaging Stress Task (MIST) is a variety of the Trier Test (Dedovic et al., 2005). It incorporates electronic mental math difficulties and social evaluative danger components with the assistance of a PC program. It is applied by an examiner. So as to have the option to separate the impacts of pressure and mental math, it has three stages (rest, control, and test). In the first test form, the subject is watched by means of practical attractive reverberation imaging (fMRI) or positron emanation tomography (PET) in these stages. In the resting stage, the subject ganders at the PC show. In this stage, subjects are not approached to play out any undertakings. In the control stage, a progression of mental number juggling assignments appear to the member and member answer the undertakings by utilizing the gave PC program. In the last stage which is the test stage, the trouble of the assignments is expanded and the time furthest reaches of the errands is diminished. The point is to build the undertaking trouble over the member's psychological capacities. To expand the pressure of the member more, the normal execution of members and evaluated finish time is shown to the subject. After the finish of each assignment, the presentation assessment is shown to additionally build the pressure of the member.

Cold Pressor Test

The cool pressor test is another cardiovascular test applied by placing the member's hand into an ice water holder for a moment (Lowery et al., 2003). It very well may be additionally used to initiate pressure. Circulatory strain and pulse are checked. The system of the test is as per the following: The subject

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of the test is approached to put his/her hand neglected pressor as long as possible. They are advised to communicate on the off chance that they feel any agony. In the event that the agony gets agonizing, they can expel their hands. This causes specialists to gauge the edge (first inclination agony) and resilience (all-out time short edge). This form of the chilly pressor undertaking is the most generally applied one.

ANXIETY SIGNALS

We can gauge and watch anxiety side effects from numerous points of view. The Sympathetic Nervous System (SNS) touches off the anxiety response (Pereira Rodrigues, 2013), bringing about mental, physiological, and conduct side effects (Kaklauskas et al., 2011). A self-report questionnaire can be used for psychological measures of anxiety or can be interviewed by an analyst (Alberdi et al., 2016). Since this section is not used in automated anxiety detection subjects. Secondly, physiological signals are evaluated for anxiety. These provide information on the strength and consistency of the subject ‘s effect and experience (de Arriba-Pérez et al., 2019). Hormones, electrocardiograms, electroencephalograms (EEGs), electromyograms (EMGs), respiration, blood volume pressures (BVP), eye look and blink, thermal imaging (TI), electro thermal activity (EDA), blood pressure (BP), skin temperature (ST), and functional magnetic resonance imaging (fMRI) are indications of concern for this review.

Another way to track tension is through behavioral changes. Pain affects people’s behavior. We can measure behavioral changes without invasive methods and the need for extra equipment. Conduct responses include characteristics of the keystroke and keyboard, stance, facial gestures, voice, cell phone use, walking habits, and linguistic writing.

ANXIETY DETECTION: LITERATURE REVIEW

We include a summary of anxiety recognition studies in the literature in this section. There have been various solutions to the issue of anxiety recognition. In other words, the former study can, due to the use of physiological signs or other behavioral properties, be split into two distinct classes. When physiological signals are used to focus on anxiety analysis, the potential signals can be clarified in conjunction with stress and their severity. The physiological signals used in this section describe cardiac activity, electrodermal activity, brain activity, speech data, camera studies and multi-modal measurement research.

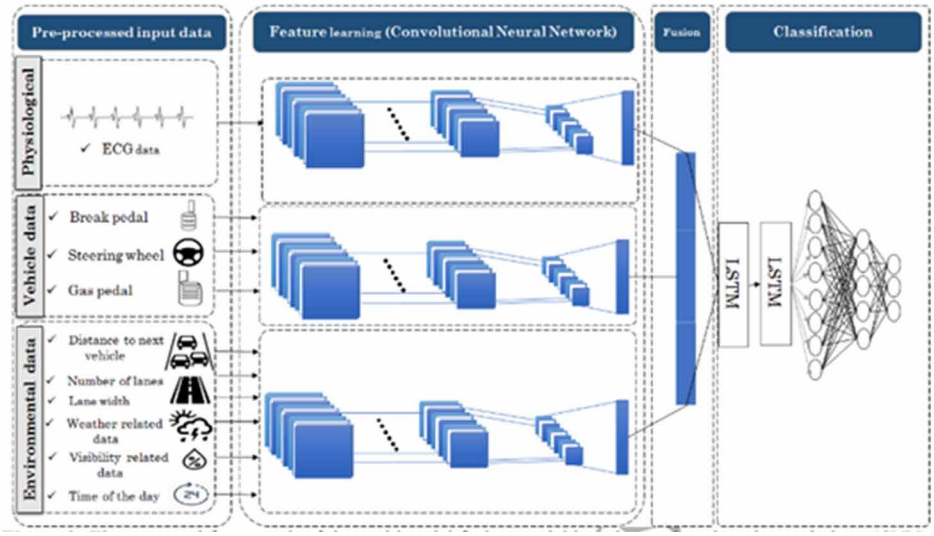
To order to gain more and more detailed details about the state of the mind, it is also important to concentrate on not only a single anatomical characteristic but all of them. In view of this multimodal approach, several articles examine and compare a range of parameters and signals.

The variation of the human body’s heart rhythm (HR) has previously been considered a stress measurement, and many researchers have incorporated this parameter into their research. The probability of sensing stress by using common wearable devices available on the market was explored according to de Arriba-Perez et al. (de Arriba-Pérez et al., 2019). the authors offer a method to estimate stresses based on the use of the shelf crumbs and machine learning techniques. To induce stress uniformly and systematically, they developed a mobile app. The app implements well-known stress inducers such as the Strop Color-Word Interference Test and a hyperventilation activity. The author used wearables (Microsoft band 2) to collect physical data used to train the classifier and to estimate the stress levels. In an experiment involving 19 participants, the solution was tested with average accuracy and an F-measurement of around

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0.99 in the person model and accuracy and F-measurement of about 0.85 in a two-level global model (Rastgoo et al., 2019). The investigators calculate the cardiovascular (HR)/screen (ST)/accelerometer (ACC) and GSR in the following physiological cues for anxiety detection. Although this was a very good work to tackle this problem, we do not think the authors used a very critical parameter known as EEG. In another study by M. N. Rastgoo et al. (Rastgoo et al., 2019) one of the leading causes of road accidents was stress. The author has tried to create practical methods to track drivers' stress levels in real-time, inspired by a need to deal with significant costs of driver stress (Rastgoo et al., 2019). They develop a system in which data are collected like ECG signals, vehicle data (such as steering wheel, brake pedal), and related data (such as weather conditions and other environmental factors). The authors apply a methodology focused on the use of deep learning techniques for the detection of driver tension collected by multimodal fusion CNN-LSTM (show in fig. 2) after data collection. In this way they achieved 95.00% accuracy in the confined position while detecting the stress of the driver (Rastgoo et al., 2019).

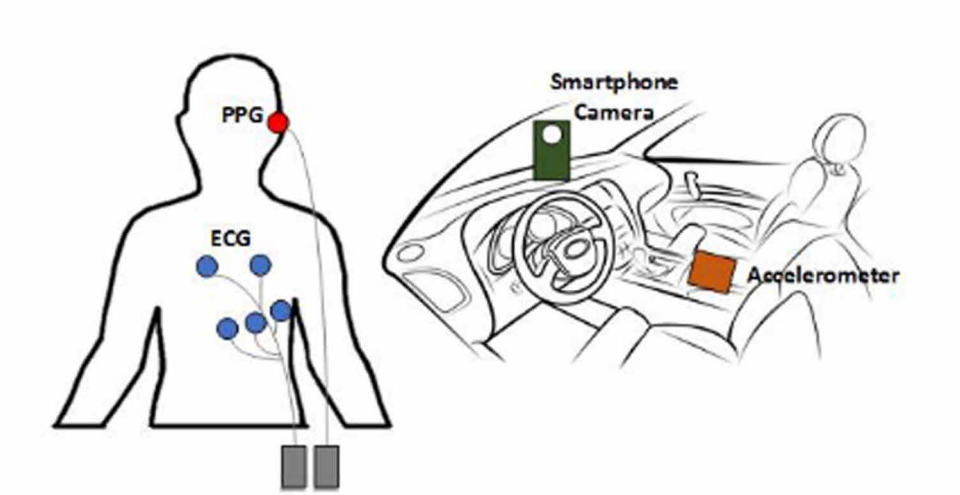
Figure 2. framework of the multimodal fusion model based on a deep learning technique (CNN- LSTM) to classify the stress level of drivers into three levels (Rastgoo et al., 2019)



Many work have taken advantage of combining various physical signals such as HRV using ECG, pulse transient time using PPG, acceleration of motion using an accelerometer. Another work by C. Dobbins (Dobbins & Fairclough, 2019) defines a variety of algorithms for the analysis of various sources of life logger information in real-world driving for the purposes of anxiety detection. The authors performed two data-gathering exercises in which multimodal data were collected from 21 people during day-to-day travel, including raw cardiovascular activity and driving information. Its methodology allowed them to 1) quantify accurate measures of heart rate variability before the process, to determine a relevant stress marker, 2) identify / correct raw physiological data objects, and 3) to compare different stress detection classifier. Here the average precision obtained in real life by using ensemble classification models was 86.9 percent binary stress identification (Dobbins & Fairclough, 2019).

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Figure 3. The participants were wearing a Shimmer3 (ECG) electrocardiogram on their face, and they clipped the Optical Pulse Ear-Clip photoplethysmogram (PPG) to their ear lug. A smartphone with the rear camera faced off the front windscreen was put in a flat pos (Dobbins & Fairclough, 2019)



Its methodology allowed them to 1) quantify accurate measures of heart rate variability before the process, to determine a relevant stress marker, 2) identify / correct raw physiological data objects, and 3) to compare different stress detection classifier. Here the average precision obtained in real life by using ensemble classification models was 86.9 percent binary stress identification (Dobbins & Fairclough, 2019).

Jiayuan he et. al (He et al., 2019) experimented and use CNN to achieve accurate and fast detection of acute cognitive stress from heart rate variability (HRV). The author uses a traditional psychiatric calculation which was taken as the stressor in 20 participants, which involved the acquisition of a one-lead electrocardiogram (ECG). The author uses six conventional HRV methods that were extracted from ECG signals for the inference of cognitive stress, and their performance was compared with the CNN-based approach in the identification of acute cognitive stress. The experimental results of this research demonstrated that the detection error rate for CNN was considerably greater with a super-short (10 s) time period than the output of all six traditional methods of HRV (> 7.2 percent $p < 0.01$) (He et al., 2019). Although the author managed to find a good result, it is very limited in terms of several parameters. We found after intensive literature that ECG circumspection alone is not sufficient to detect levels of anxiety.

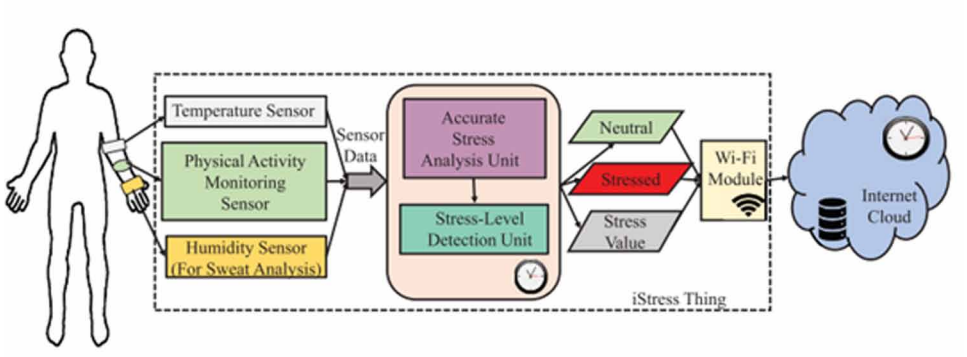
M. wang et. al (Wang et al., 2018) discuss the BCI smart helmet guidelines for anxiety disclosure and method of identification. The author proposes to use the EEG rhythm and a fusion algorithm of anxiety level to evaluates the anxiety status of a minor. Includes the stress level mental parameters, stress level, concentration level, and environmental mine parameters. Experiments conducted by the author revealed that Fp2 is the optimal location to reach the intensity parameter of anxiety. In the first 2s after excitatory work, the most pronounced EEG changes are seen. Rhythm amplifiers more clearly increase negative emotion (Wang et al., 2018). Another research by Stefano et. al (Betti, 2018) with aims to improving and evaluating the capacity of an ECG, EDA and EEG-based wearable physiological sensors device to monitor human stress and determine whether the changes in physiological signals that have been observed are associated with changes in the salivary cortisol level, which is the reliability of an analytical stress biomarker. in this research 15 medical students, seven male and six female, mean age 40,8 < formula >

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< tex > $\pm$ < /tex > < /formula > 9.5 years, used the Maastricht Acute Stress Test as a set of three business sensors, known for producing robust physical and mental stress. Saliva samples have been obtained by the author during various stages of testing. Statistical analysis an attempt has been made to find the causes of stress using the classification algorithm for a support vector machine (SVM) (Betti, 2018).

According to Hong et. al (Liu et al., 2018), Anxiety is some form of extremely negative feeling, and the source of many significant physical and mental disorders is long-term anxiety. A high-detection precision can be achieved in certain scenes through anxiety detection based on autonomic nerve patterns. The author designed four different motions intensities for analyzing the autonomic nerve activity of typical motion states and identified motion conditions with a similar autonomic nerve pattern to the anxiety status. they established a multi-modal in-house anxiety management system (Liu et al., 2018). Laavanya et. al (Rachakonda et al., 2018) present a novel stress monitoring system that is suggested, iStress, which measures anxiety rates during physical activity by body temperature, motion rate, and sweat. this system is implemented using a neural network approach using a fluid logic controller of the Mamdani type, which consists of more than 150 different models.

Figure 4. Architecture of the iStress System (Rachakonda et al., 2018)



Purnendu et. al (Pandey, 2017) say we can tell whether a person is depressed or not based on heart rhythm. they used the heartbeat rate as one of the parameters to identify the tension previously. Things (IoT) with machine training (ML) is used for forecasting the patient's condition and monitor the patience of acute stress. This research finds a correlation between age and heart rate with 50–80% accuracy (Pandey, 2017). D. Lee et. al (Lee et al., 2017), a wearable device for sensing driver tension in real-time is being developed. In this article physical signals and a control wheel speed analysis calculate driver anxiety. The driver's handheld app analyzes the direction of the steering wheel. The glove-mounted sensor mainly collects the photoplethysmogram signal via the fingers and signals the movement of the hand through the passive movement device. In order to measure the driver's anxiety level, the author then transmitted the reading of the sensor panel to the final terminal device using the lower energy transmitting panel Bluetooth. This research was performed in Simulated Driving, which consists of three separate motor situations for studying the actions of stress-related subjects. Throughout this study, twenty-eight participants were demanded and three separate driving sessions of random scenarios were carried out to test the mental labor level. Assessment of the tension of test participants by self-expression during the

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study as well as after the self-reported stimulus. in this study, more than 95% of findings were reported on average using the anxiety index of a vector machine pattern classification (Lee et al., 2017).

SUMMARY

Anxiety is a very complicated problem and it isn't a straightforward job to quantify it. Many markers can be used, numerous algorithms can be used and many types of stress are observed. In this paper, we are going to present a variety of comparisons, such as which physiological signals are very important to detect anxiety, comparison between different algorithms to detect anxiety, what is the limitations of solutions available, etc. Table 1 represents various scientific publications related to anxiety and physiological signals.

Table 1. Scientific publications relating stress and physiological signals

Bibliographic Ref.	BP/BVP	ST	HR/HRV	GSR	EEG	Acc.
(de Arriba-Pérez et al., 2019) (2019)		√	√	√		√
(Rastgoo et al., 2019) (2019)			√			
(Dobbins & Fairclough, 2019) (2019)	√		√			√
(He et al., 2019) (2019)			√			
(Wang et al., 2018) (2018)					√	
(Betti, 2018) (2018)			√	√	√	
(Liu et al., 2018) (2018)			√			√
(Rachakonda et al., 2018) (2018)		√		√		√
(Lee et al., 2017) (2017)	√			√		

With the help of the above table, based on our literature we are trying to confirm how various physiological signals are playing an important role in anxiety detection. This study proves that various researchers use wearable devices to detect anxiety using a variety of physiological signals such as heart rate variation (HRV), galvanic skin response (GSR), skin temperature (ST), Blood pressure (BP), electroencephalogram (EEG), and an accelerometer (ACC).

Our study also shows how different types of physiologic signal sensors can work and what type of information can be collected by them. Table 2 represents the information of the sensors used to collect physical signals.

Another comparison of various scientific publications of machine learning algorithms for anxiety detection is presented in Table 3. Here we are trying to represent a comparative study between different types of machine learning algorithms in terms of accuracy based on different types of physiological signals.

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Table 2. Physiological signals sensor information

Sensor	Details	Frequency
Accelerometer	Provides X, Y, and Z acceleration in g units. 1 g = 9.81 meters per second squared *(m/s^2)*	62/31/8 Hz
Heart Rate	Provides the number of beats per minute	1 Hz
ECG	Measure the electrical activity of the heart	1 Hz
Skin temperature	Provides the current skin temperature of the wearer in degrees Celsius	1 Hz
Galvanic Skin Response	Provides the current skin resistance of the wearer in kohms	0.2/5 Hz
PPG	It can be used to detect blood volume changes in the microvascular bed of tissue	0.5/4 Hz
EEG	An EEG tracks and records brain wave patterns	250/2000 Hz

Table 3. Comparison of various scientific publications of machine learning algorithms for anxiety detection

Bibliographic References	Physiological Signal	Machine Learning Technique	Accuracy (%)
(de Arriba-Pérez et al., 2019) (2019)	ST, HRV, GSR, Acc.	NN, SVM, RF, IBK, C4.5	78.85%
(Rastgoo et al., 2019) (2019)	HRV, Acc.	CNN-LSTM	92.8%
(Dobbins & Fairclough, 2019) (2019)	BP, HRV, Acc.	LDA, DT, kNN	86.9%
(He et al., 2019) (2019)	HRV	CNN, LDA, SVM	72%
(Betti, 2018) (2018)	HRV, GSR, EEG	SVM	86%
(Liu et al., 2018) (2018)	HRV, Acc.	SVM	80%
(Rachakonda et al., 2018) (2018)	ST, GSR, Acc.	Mamdani-type fuzzy logic controller	91%
(Pandey, 2017) (2018)	HRV	LR, SVM	67%
(Lee et al., 2017) (2017)	BP, GSR	SVM	92%

The above table represents a comparison between different types of algorithms such as the research by F. de Arriba-Pérez et al (de Arriba-Pérez et al., 2019) that have used ST, HRV, GSR and ACC physiological signals. And they achieved 78.8% accuracy using the above signals by applying machine learning algorithms like NN, SVM, RF, IBK and C4.5.

PROPOSED WORK

Anxiety treatment is a complex task. Recent wearable sensory innovations have been used to track physiological data for anxiety diagnosis and to reduce anxiety when needed. We have proposed a model for anxiety detection. Physiological data such as heart rate, EEG, ACC, and skin temperature, the level of sweat, are jointly used to detect the anxious state. Using this type of approach will produce greater accuracy.

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CONCLUSION

Anxiety in contemporary culture is a significant problem and has social and economic ramifications. Work in controlled laboratory settings has started and studies for the measurement of stress are highly effective. Since the everyday levels of anxiety in laboratory environments can nevertheless be dramatically different (Hung & Picard, 2016), regular tests in the scientific community have become very common. The idea that consumers don't like excessive measuring methods in laboratory settings is often an important explanation for everyday anxiety detection studies. IoT devices and unobtrusive mobile apps can be used without distressing people to assess tension rates in daily life. In this section, we discussed challenges of open research for the detection and improvement of anxiety in daily life. The accuracy of daily anxiety monitoring systems is also slightly lower than the quality of the lab settings. In anxiety analysis, the ultimate aim is to build a high precision scheme in everyday living by unfinished problems and emotional regulatory approaches to reduce users' tension.

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Chapter 4
Applied Intelligence for Medical Diagnosing

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ABSTRACT

Medical imaging is associated with different techniques and processes that are used to create visual representations of internal parts of the human body for diagnostic and treatment purposes within digital health. Machine learning plays a crucial role in the medical imaging field including analysis of various medical images, computer-aided diagnosis or detection, image retrieval, gene data analysis, image reconstruction, and organ segmentation. The machine learning algorithm framework recognizes the best combination of the medical image features for categorizing the medical images or processing some metric for the given image area. The images obtained are then processed using algorithms such as K-means, support vector machines, decision trees, neural networks, and deep learning techniques.

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INTRODUCTION

Medical imaging plays a pivotal role in diagnosing diseases. It helps doctors, physicians to detect the diseases at early stages and give necessary prescriptions. This helps in reducing the overall cost of treatment and also saving human lives. Among all the techniques, Digital Infrared Thermal Imaging also known as Medical Thermal Imaging or Thermography is a valuable method to notify the clinicians about the changes that can indicate the early stages of diseases, which is crucial for patients. Digital Infrared Thermal Imaging is a non-invasive imaging method that collects thermal information using thermal imaging devices. It can also be defined as a method that detects infrared energy that is emitted from an object and this energy is converted into a temperature and an image is displayed which represents the temperature distribution. Last few decades have seen an increasing trend in using Artificial Intelligence for everything due to its many advantages. It can easily identify a variety of trends and patterns, minimal human intervention is needed, the continuous scope for improvement and handles multi-dimensional data effortlessly. Artificial Intelligence can now be particularly helpful in diagnosis of diseases considering the many advancements in the field. Machine Learning combined with thermography for the detection of diseases can be a very effective tool. Objective of this chapter is to show various medical imaging strategies, image preprocessing techniques and machine learning techniques like K-means clustering, Support Vector Machines, Decision Trees, Neural Networks and Deep Learning.

INTRODUCTION TO MEDICAL IMAGING

Medical imaging means using different technologies and processes to observe the interior of the man's body to diagnose and treat diseases. The field of medicine has been transformed by medical imaging. Imaging remains one of the fastest-growing sources of medical data more than a century after its inception. Medical Imaging has revolutionized the Health and Wellness Industry, allowing doctors to recognize and treat diseases more efficiently. Medical imaging can even detect diseases before we can feel them. When an imaging study of the internal structure of a human body is performed, it can have a variety of benefits as the analysis and integration of the images provides vital information about the functioning of the body.

Medical Imaging comprises many radiological imaging methods:

- **Radiography**
- **Fluoroscopy**
- **CT Scan**
- **Tactile imaging**
- **Medical ultrasonography or ultrasound**
- **Endoscopy**
- **Magnetic resonance imaging (MRI)**
- **Elastography**
- **Medical photography as well as nuclear medicine functional imaging techniques like positron emission tomography (PET).**
- **Thermography**

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1. **Radiography:** X-Rays, gamma rays, and other forms of ionizing and non-ionizing radiation are used in radiography to see through any object (Radiography, 2020). Figure 1 shows radiography which uses X-rays for imaging. The output is in the form of a static image. It is generally used for dental examinations, orthopedic and chiropractic examinations. A few of the risks of Radiography include over-exposure to radiation, if the patient is pregnant it can be harmful to the fetus too.

Figure 1. Radiography

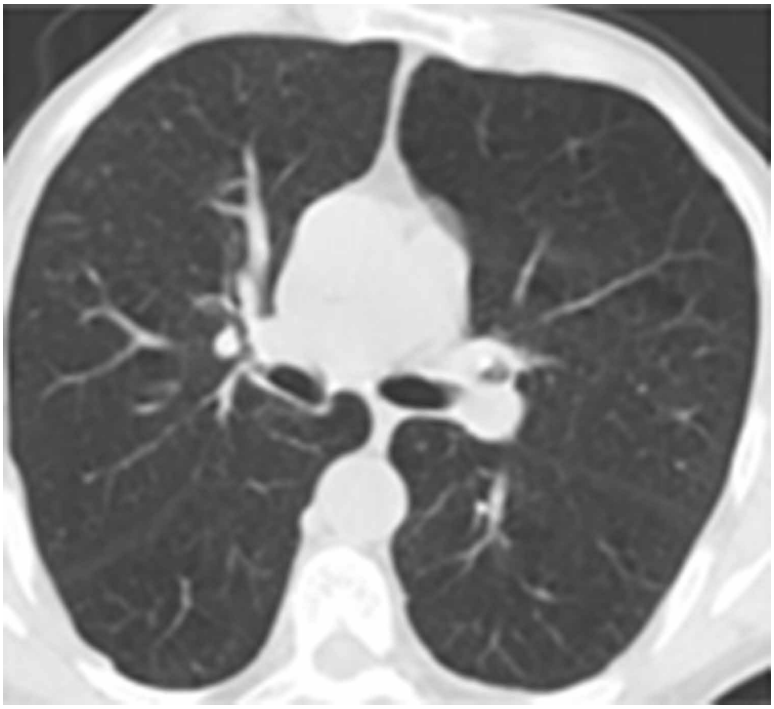


2. **Fluoroscopy:** Fluoroscopy is the study of moving body parts. The machine used is called C-Arm, which gets its name because of its prominent C shaped arm. The patient is exposed to a continuous beam of X-Ray during fluoroscopy, and the result is a continuous X-Ray image that looks like an X-Ray movie. The footage is subsequently transferred to a monitor, which displays the parts of the body and its motion. The part that is to be examined is injected with an X-Ray dye or contrasting agent Barium Sulphate which is a white chalky substance (Fluoroscopy, 2020). Contrasting agents help to distinguish the body parts with precision. There are certain risks associated with fluoroscopy, as do other X-Ray procedures. While performing complicated procedures, the patient can be exposed to relatively higher doses of radiation. Radiation-induced risks include skin and tissue burns. If radioactive dye is used, there is a chance of an allergic reaction. However, the possibility that the patient suffers from these side effects is statistically very low and is outweighed by the advantages it provides.

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3. **CT-Scan**: A computerized tomography (CT) scan is used to obtain multiple-angle pictures of organs. After that, a computer is used to construct a cross-section of the body's bones, blood arteries, muscles, and soft tissues. It is generally performed to detect fractures, muscle disorders, infections, internal injuries and bleeding (Ross, 2016). The amount of radiation is higher than most other X-Ray techniques hence it is recommended only when absolutely necessary. Similar to other radiographic tests CT scans also can be harmful to fetuses.

Figure 2. CT-Scan



4. **Tactile imaging:** Tactile imaging is a process that converts the sensation of touch into a digital image. Different tissue features such as elasticity can be detected by palpating them side by side, but the human finger cannot tell if they are separated in time or space. The brain has trouble remembering the finer points of tissue flexibility. A special probe can be used to palpate the tissues, which measures the pressure versus tissue displacement. The software then creates a digital image, which allows it to quantify tissue elasticity and calculate the local young's modulus (Mechanical Imaging and Tactile Imaging, n.d.). The tactile image is a function of P(x,y,z), where
   P = pressure on soft tissue surface under applied deformation
   x,y,z = coordinates where pressure P was measured.

Muscle activity is converted into a dynamic pressure pattern with Functional Tactile Imaging. P(x,y,t) for a region of interest, where:

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t is time
x,y are coordinates
P is the pressure that was measured.

It might incorporate:

a. Specific maneuvers
b. Involuntary relaxation
c. Involuntary reflex contraction
d. Muscle voluntary contraction

Changes in mechanical properties such as soft tissue elasticity, structure support, muscle mobility, and contractile strength are seen in a wide range of organ or tissue disorders and diseased conditions. As a result, biomechanical mapping of a human organ or tissue of interest offers up new possibilities in the following areas:

a. Medical Imaging
b. Diagnostic
c. Targeted treatment
d. Monitoring

This technique is particularly useful for identifying and diagnosing pathogenic disorders in the female pelvic floor, as well as pathologies, spontaneous preterm delivery, and maternal birth trauma.

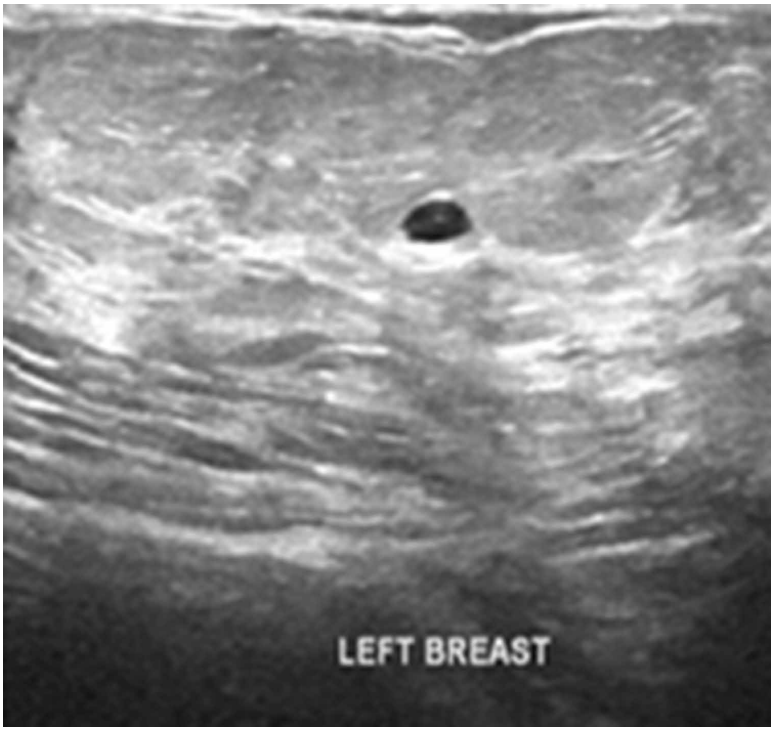
5. **Medical ultrasonography or ultrasound:** Ultrasound or high-frequency sound waves are utilized to produce a picture in medical ultrasonography. It's also known as an ultrasound or a sonogram. The sonographer holds a transducer that emits ultrasound. The ultrasound then travels through the soft tissues, fluids, and bounces back when it hits denser surfaces. A computer then translates these ultrasound echoes into an image. It is a non-invasive test and has almost no complications. The ultrasound is practically harmless and has no side effects when used externally on the skin. The ultrasound can disrupt or irritate tissues with prolonged exposure but the computer adjusts the intensity to minimize the risk. Figure 3 and Figure 4 doesn't have and has tumor respectively.
6. **Endoscopy:** This technique is carried out using an endoscope, which is a long thin tube with a camera and light connected to it. The camera is connected to a screen and can be used to take pictures as well as videos (DerSarkissian, 2019). It is a minimally invasive technique, the endoscope can be inserted into small openings like the mouth, colon, and ears. Sometimes small incisions are made on the patient's body especially for endoscopy. Modern endoscopes can give extremely detailed images and are very safe. Few potential complications are bleeding and infections. Figure 5 Shows an Endoscopy image.
7. **Magnetic Resonance Imaging:** In order to generate pictures, Magnetic Resonance Imaging (MRI) uses high magnetic fields, computers, and radio waves. Because MRI does not require ionizing radiation, it is often utilized in hospitals and clinics. It is used to find fractured bones, blocked blood vessels, brain injury, spinal cord injuries, etc. Patients with non-removable metal implants cannot be candidates for MRI. It involves going into a narrow tube that can be very uncomfortable

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for people with claustrophobia. The MRI machine makes much more noise and also takes longer than a CT scan machine which may cause some discomfort. If the patient is not still during the whole process the images can come out blurred. Figure 6 and Figure 7 show brain without and with tumor respectively.

8. **Elastography:** Elastography is used to find the stiffness of the tissues. It is a non-invasive technique that administers low-frequency vibrations to the tissue, then an MRI or CT scan is used to see how quickly these vibrations travel through the tissue. A computer is then used to map the stiffness of the tissues onto an image. The softness and hardness of the tissue can give valuable insights for diagnostics. It can be used instead of invasive techniques like biopsy in certain cases. It doesn't involve exposure to any harmful ionizing radiation.
9. **Positron Emission Tomography:** PET scan is a technique for revealing how tissues and organs function, as well as showing cellular activity within the body. The radiation released by the tracer is detected by a PET scan machine. A tracer is a radioactive substance that is fused with a natural chemical like glucose. The tracer can be swallowed or injected depending upon the organ under supervision. The tracer is carried to cells that use glucose as an energy source. It gets collected where there is more chemical activity which is usually the infection. Hence on the PET scan, that area appears brighter than the surrounding areas. It is done to detect cancers, heart and brain disorders. As the tracer is radioactive, it can cause an allergic reaction. Patients are recommended to drink lots of fluid to flush the tracer, it should not remain in the body for more than 2-3 hours. It is not recommended for patients who are pregnant or breastfeeding.

Figure 3. Ultrasound without tumor



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Figure 4. Ultrasound with tumor

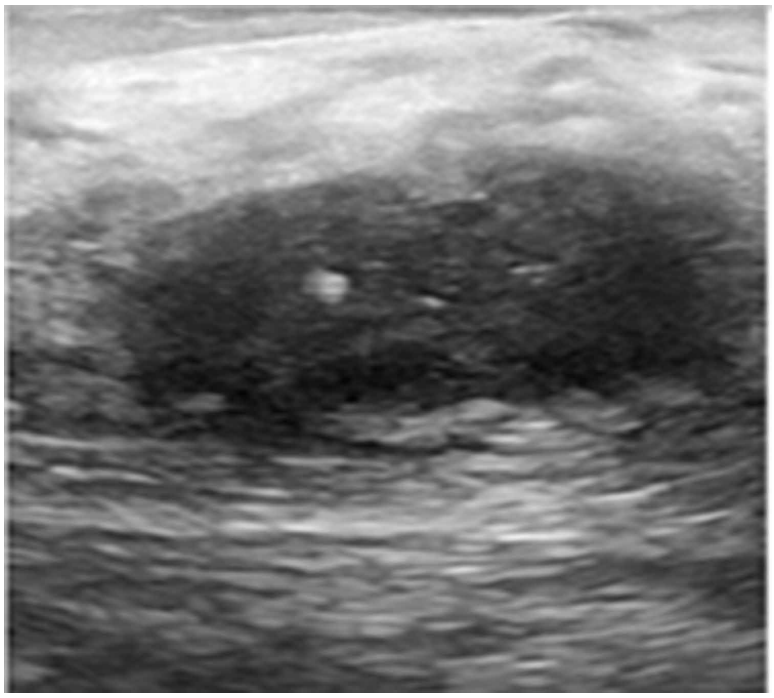
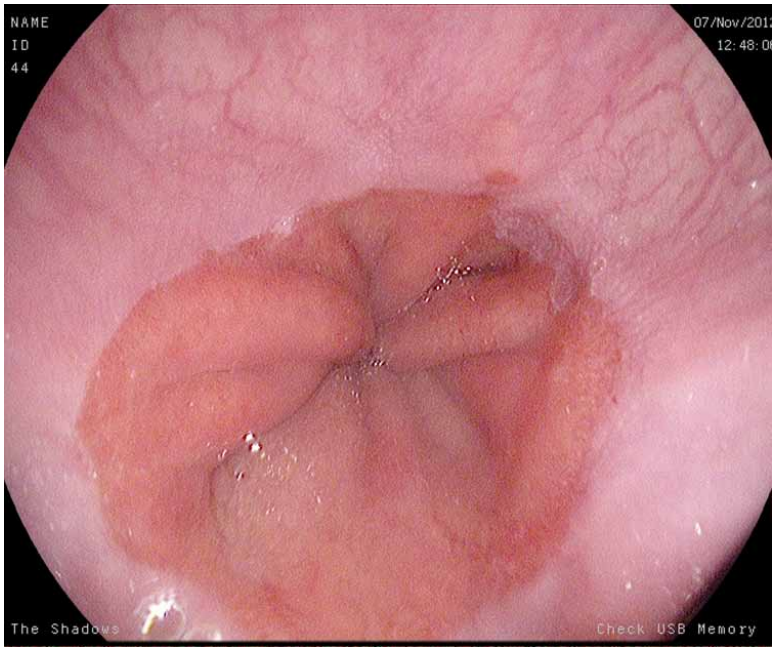


Figure 5. Endoscopy



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Figure 6. MRI of a normal brain

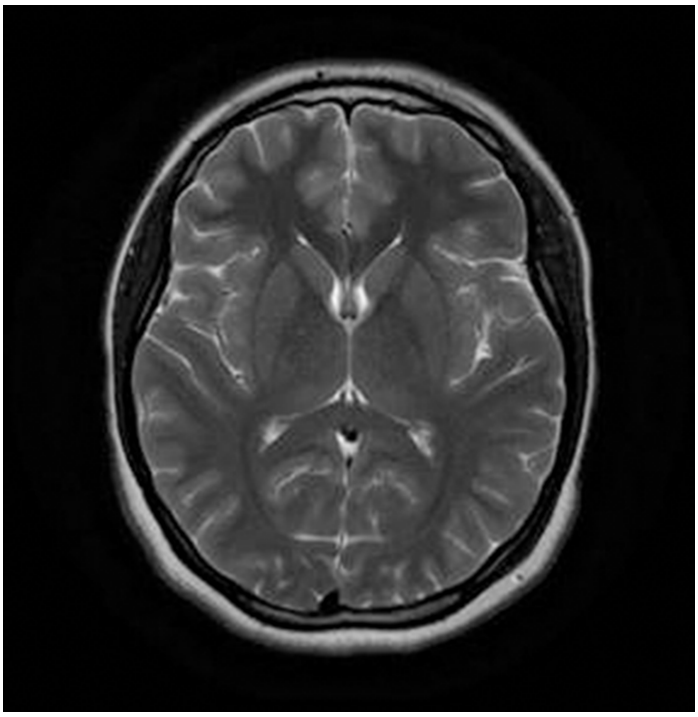
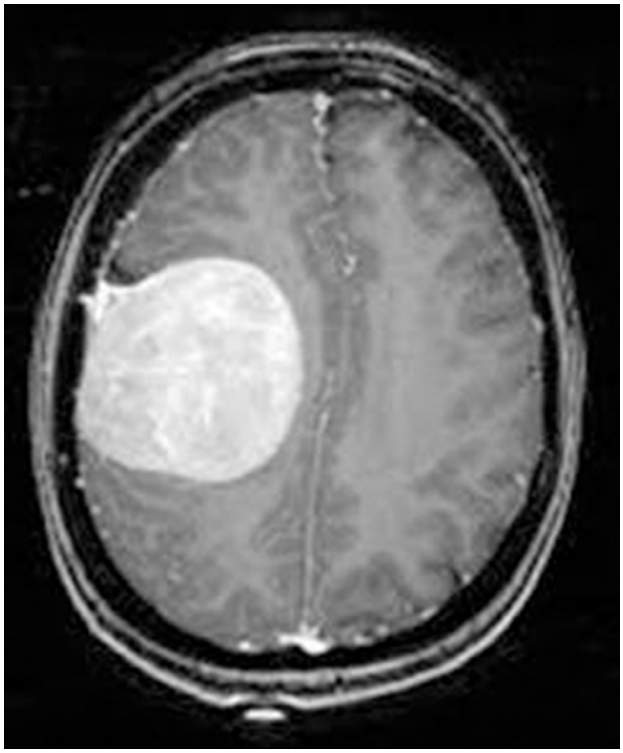


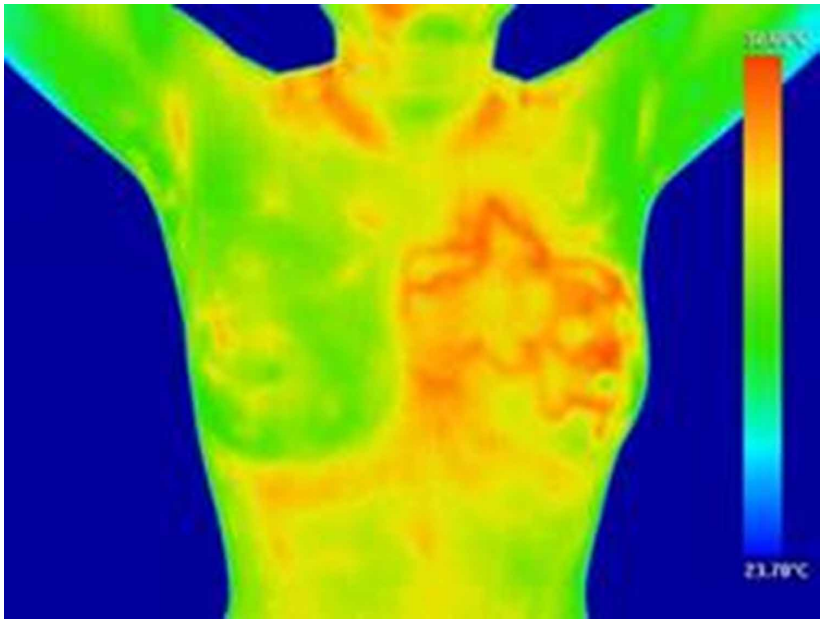
Figure 7. MRI of brain with tumor



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10. **Thermography:** Thermography is the image produced by sensing the heat released by the body. For performing thermography infrared cameras are used which detect the heat released and the blood flow of the body part of which image is to be produced (Ross, 2016). Thermography is majorly divided into two types based on the heat source:

Figure 8. Thermograph



a. Active Thermography

It measures the temperature at the surface for evaluation following thermal excitation. A source of energy is required in order to create a temperature difference between the feature of interest and its surroundings. The portions that are being examined are in equilibrium with the surrounding environment.

b. Passive Thermography

Since the features of interest are naturally at a lower or higher temperature as compared to the surroundings, the temperature at the surface is directly measured for evaluation.

Advantages of Medical Imaging

In the last 30 years, medical imaging or diagnostic imaging has been a boon to the medical industry. It allows us to identify diseases in the early stages and improve the outcomes for patients drastically. It is beneficial for diagnosing diseases that do not exhibit any kind of symptoms.

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1. **Improved diagnosis:** With the help of medical imaging, doctors can get a much better view of what's going on in the patient's body and it also helps the doctors make better decisions about the patient's treatment and surgery.
2. **Painless diagnosis:** In most diagnostic imaging procedures, special preparation is not needed and these procedures are painless and non-invasive. For example, with the utilization of ultrasound innovation, the specialist can see your infant, determine any abnormalities and check its advancement during pregnancy. It is probably the best strategy accessible to screen an unborn infant.
3. **Reasonable Health Care Costs:** When the specialist recognizes what/where the issue is, he can make a better decision on further treatment. For instance, atomic medication tests can identify heart conditions before they deteriorate to the point of requiring a medical procedure. Illnesses and conditions trapped in the late stages ordinarily require more comprehensive treatment or surgery, which regularly accompanies greater expenses and difficulties. If proper treatment is provided at the beginning, then this radically reduces health care costs.

Table 1. Comparison of different technologies

Techniques	Invasive	Radiation	Early Detection	Cost of Detection	Accuracy
Radiography	No	Yes	No	Inexpensive	Highly Accurate
Fluoroscopy	No	Yes	Yes	Inexpensive	Accurate
CT Scan	No	Yes	Yes	Moderately expensive	Highly Accurate
Tactile Imaging	Yes	No	No	Less expensive	Moderately Accurate
Ultrasound	No	No	Yes	Moderately expensive	Highly Accurate
Endoscopy	Yes	No	No	Moderately expensive	Highly Accurate
MRI	No	No	Yes	Expensive	Highly Accurate
Elastography	No	No	No	Expensive	Accurate
PET Scan	No	Yes	Yes	Expensive	Highly Accurate
Thermography	No	No	Yes	Moderately expensive	Most Accurate

Advancements in Medical Imaging

Medical imaging has evolved in digital and communication technology in recent years. New imaging methods that uncover prominent anatomical details are accessible easily. High resolution Computed Tomography replaces the regular CT scan technology and it generates more clear images with higher spatial resolutions. The few major advancements that showcase the future scope of medical imaging technology are:

1. **Open portable and silent MRIs**: The machines have wider openings which results in the patients feeling less anxious.
2. **Big Data and Analytics**: Digitally storing data of large volume, velocity and variety and analyzing is big data and analytics.

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3. **Digital mammography**: Instead of X-rays a digital receptors and computer are used to have a special form of mammography image which examine breast tissue more accuracy.
4. **Artificial Intelligence**: Enabling computers and machines to mimic learning, problem solving and decision making capabilities like humans. In data (images, numerical), ANNs may discover complicated nonlinear relationships between dependent and independent variables that humans may fail to detect.
5. **Augmented Reality**: With the help of different visualization sensors and imaging the actual physical world is stimuli via technology. It is used in various clinics for vein visualizations, surgical visualization and education.
6. **Cinematic Rendering**: Rendering, also known as image synthesis, is the process of using a computer software to create a photorealistic or non-photorealistic picture from a 2D or 3D model.
7. **Image Fusion**: Image fusion is a method of combining numerous pictures into a single more informative image.
8. **Three Dimensional Printing**: Also known as additive printing is a process in which a 3D solid objects are made from a digital file using a plastic. It is used to make models for diagnosing diseases, pre-operative planning and to make personalized medical devices and implants.

With the new computerized imaging modalities, the management and sharing of images have become efficient and effortless.

DIGITAL INFRARED THERMOGRAPHY

The word Thermography is made up of two words Thermo and Graphy. Thermo means heat and graph means graphical image. Hence, by using thermography an image can be produced by sensing the heat released by the body. For performing thermography, infrared cameras are used which detect the heat released and the blood flow of the body part of which image is to be produced.

There are two types of cameras used for thermography:

- **Single sensors**
- **Focal Plane Array (FPA)**

In a single sensor, there is a rotating mirror that has a single sensor used for capturing images.

FPA stands for Focal Plane Array in which arrays are used to detect the radiated point and provide information.

The sensitivity of these cameras is extremely high i.e. from 1,000 nanometers to 14,000 nanometer which is 1 micrometer to 14 micrometers which can be compared to an ordinary visible-light camera that can only sense 400 nanometers to 700-nanometer range.

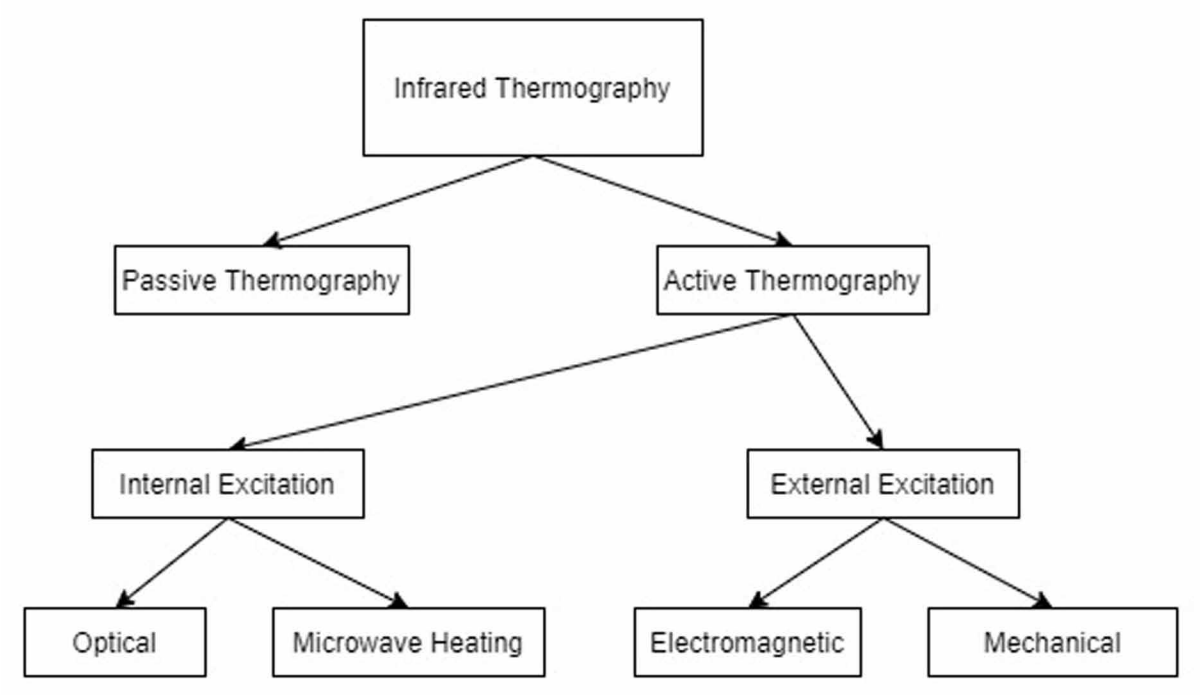
Figure 9 shows that thermography is majorly divided into two types based on the heat source Passive and Active thermography. Active thermography is further divided into two types depending on the method of excitation. Internal excitation can be achieved optically or with microwave heating and External excitation can be accomplished mechanically or using electromagnetic properties.

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Table 2. Diagnosis of diseases by different technologies

Techniques	Diseases diagnosed
Radiography	Alzheimer's, Brain tumors, Appendicitis, Arthritis, Crohn's disease Kidney failure
Fluoroscopy	Diagnose and treat blood vessel, bone, joint, digestive, urinary, respiratory, and reproductive system disorders.
CT Scan	Cancer, heart disease, emphysema, or liver masses, tumors
Tactile Imaging	Endometriosis, adenomyosis, and uterine fibroids, as well as cervical and ovarian cancer
Ultrasound	determine the reasons of pain, inflammation, and infection in the internal organs of the body, and identify cardiac problems
Endoscopy	Tumors or polyps from the digestive tract, diarrhea.
MRI	Tumors, breast cancer, diseases of the liver, heart diseases
Elastography	Fatty liver disease and fibrosis.
PET Scan	Cancers, heart disease and brain disorders
Thermography	Breast cancer, tumors, extra cranial vessel disease, neuromusculoskeletal diseases, and lower extremity vascular disease

Figure 9. Classification of thermography



1. **Passive Thermography:** Body parts are bifurcated in passive thermography based on background surface temperature, i.e. body portions with a greater or lower temperature. The temperature of the features of interest is already greater or lower than the ambient temperature. Hence the temperature is directly measured for evaluation.

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2. **Active Thermography:** In active thermography, the energy source is required that emits heat to get the required thermal contrast. Here the parts under inspection have a temperature similar to the background. Every material has different thermal conductive properties. Active thermography uses this, the defects or flaws are detected by their inconsistent heat transfer patterns. The techniques of active thermography are as follows:
   a. Internal Excitation
      i. Optically Heating

This method of Active Thermography refers to the use of man-made sources of light like lasers to excite the target. A timer coordinates the viewing cycle to the cycle of the heating stimulus. This allows viewing the object temperature when it is in a detectable steady-state.

      ii. Microwave Heating

Microwave heating is the newest of all thermography techniques. It is used to increase the hypodermic temperature distribution under some specific medical conditions. After many medical experiments, it is found that this technology can be used to a large extent in the medical field at a certain time for assessing disease. It is used for prediction and monitoring the temperature during the remedial period of hyperthermia. Hyperthermia happens when the heat-regulating mechanism of the body fails to control and there is an abnormal increase in the temperature. Many different frequency ranges are used for detection purpose on different scales. In Edrich's radiometer, the 17GHz frequency is used while in Mammonius and Ludeke radiometer 3GHz frequency is used.

   b. External Excitation
      i. Electromagnetic

Material properties such as thermal, electric conductivity and magnetic permeability are used to identify and examine the features of interest. Infrared cameras are used to detect the waves that lie in the electromagnetic spectrum which is then used to create thermographic images. This image produced in this fashion is known as thermograms. It allows us to measure temperature meticulously without any contact with the object. It can examine the object without having to slice/ break it.

      ii. Mechanical

Vibrothermography is a technique that comes under the mechanical module. Vibrothermography is also known as ultrasound thermography. In classical ultrasound thermography, a transducer is placed in contact with the specimen. Some amount of waves travel through the specimen and the rest is bounced backed to the surface. A transducer is placed on the opposite side to detect the transmitted waves and one is placed on the same side to collect the echoed/ rebound waves. Any defect, imperfection will lead to scattering, absorption and distribution of waves. This leads to a change in temperate which is then recorded using an Infrared camera. Ultrasonic waves are ideal for this because they are inaudible to humans.

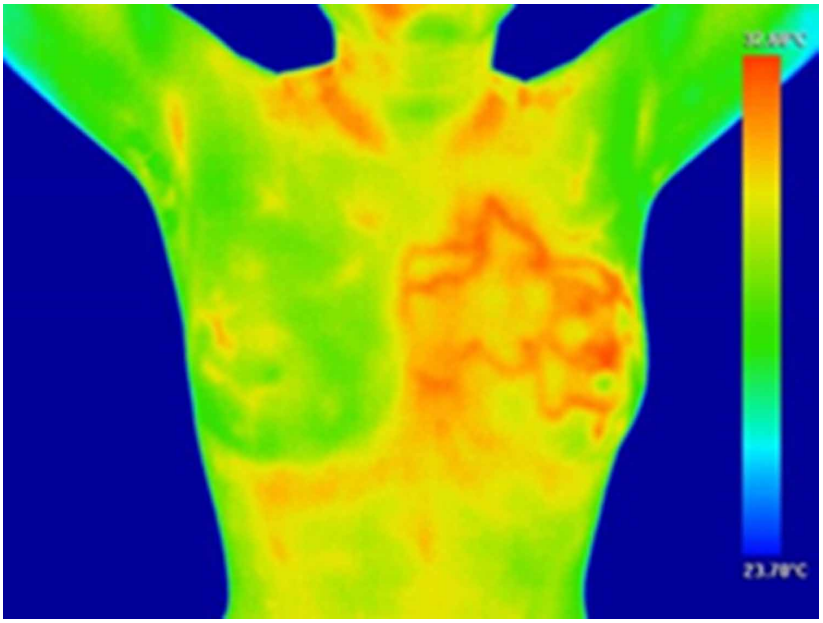
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Infrared Vision

Infrared vision is the capability to detect infrared radiation by biological and artificial systems. The human body is generally warmer than the surrounding and hot bodies release more infrared energy than the cooler ones so it's easy to produce energy. When the body gets affected by cancer disease the body cells start to multiply rapidly which require more oxygenated blood to grow. When this oxygenated blood flows through the cells and tissues the temperature of that region increases due to its large consumption, as a result, the temperature of that region increases.

The infected part uses more blood as it needs nutrition to grow. Since the blood flow is higher near the infected part it is hotter than other neighboring organs and parts. In Figure 10 we can see that infected part (left breast) has a bright red color as it has a higher temperature than rest of body.

Figure 10. Thermograph



Applications of Infrared Thermography

One of the major uses of thermal imaging is its medical diagnostic assistance. Infrared thermography is being used extensively in medicine for diagnosis of diseases as it is a fast, passive, non-invasive and non-contact method for mapping body surface temperature remotely. A correlation can be obtained between thermal physiology and skin temperature using thermal imaging cameras.

It's utilized to diagnose gynecology, kidney transplantation, dermatology, cardiology, neonatal physiology, flu testing, and brain imaging disorders. High-resolution thermographic pictures may now be acquired in real time because of developments in current infrared cameras, data gathering systems, and processing methods.

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Some of the diseases that can be detected by Digital Infrared Thermography are:

1. **Extra-cranial Vessel Disease:** Blood flowing from the neck and head have a very narrow passage and less space to be transferred, which can easily be visualized by thermal imaging. This visualization helps for predicting vascular disease which may lead to stroke when performing thermography.
2. **Neuro-Muscolo-Skeletal:** Thermography is used for diagnosing the patient suffering from back, neck and extremity disorder. Images produced are many used by chiropractors, neurologists and orthopedists to check spinal injuries in the 1970s and 1980s.
3. **Lower Extremity Vessel Disease:** Thermography is used to detect the deep vein thrombosis (i.e. blood clots block your blood vessels). Without any pain and with extreme safety it is possible to detect the disease which if neglected may result in the loss of one's limb in severe scenarios resulting in a stroke.

E.g. A person having extremely cold feet thermography; the feet temperature is always 1 or 2 degrees less than the lower leg. Toes are not visible to the camera as they become hypothermic.

4. **Breast pathologies:** The major application of thermography is in the field of breast cancer, fibrocystic breast disease, mastitis, benign tumor. Monitors which are used for viewing the image are of different types; they are full color, greyscale and isotherm temperature mapping. Cursors are used to map the point of interest with the measure of temperature which ranges from 10-degree Celsius to 55-degree Celsius with the precision of 0.1-degree Celsius.

Advantages of Thermography

- There is no harm in taking this test since there is no radiation give back which is seen in other detection processes such as X-ray (Benefits of Medical Thermography, n.d.).
- Early detection of cancer is possible.
- Women under the age of 40 or women having dense breasts can also go for thermography which is not possible in some imaging techniques like mammography.
- It is painless and less expensive.
- Women who are on hormone replacement therapy can go for this test without any fear.
- Can be helpful in monitoring the hormonal balance.
- It is a non-invasive procedure and takes very little time.
- It is safe for all age groups, and even for pregnant women.

Disadvantages of Thermography

- Thermography is less sensitive than mammography (Antwerp, n.d.).
- The false-positive rate for detecting anomaly is high, which means even though the patient doesn't have any kind of anomaly still sometimes the obtained image says that the patient is suffering from some anomaly.
- Due to high temperature in the breast area indicate cancer but sometimes it's not, mastitis which is not a cancer-causing symptom can be miss predict
- Only 84 percent of the time the result showing patient having breast cancer is right

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- The camera is not useful for conducting screening below -50 degree Celsius
- The camera used for producing images has an accuracy of only +/- 2 per cent.

MACHINE LEARNING FOR MEDICAL DIAGNOSIS

Artificial intelligence (AI) is a discipline of computer science concerned with the creation and programming of machines that have human intellect. The machines are modeled in such a way that they can think, learn, plan, copy actions and solve problems like humans. Artificial intelligence these days is everywhere; used to suggest what you should purchase online next, to understand what a person is trying to say to virtual assistants, for example, Amazon's Alexa, Apple's Siri, Google Now, and Microsoft's Cortana. There are endless possibilities where Artificial Intelligence is being applied like GPS, self-driving cars, content recommendation, robotics, etc.

Machine Learning is a subset of Artificial Intelligence that involves building models and programs that learn from their own experience. Since they learn from experience they only get more accurate with time. Machine Learning is further classified into three parts.

1. **Supervised Learning:** The machine learning algorithm is trained on labelled data in this case. Despite the fact that precise labelling of data is required for this approach to operate, supervised learning is incredibly effective when employed in the proper situation. In supervised learning, the algorithm is given a dataset that is split into two sets of training data and testing data. The training and testing data are usually divided into 80:20 ratio, however this might vary from problem to problem. The system then searches the training data set for relationships between the specified parameters. The algorithm understands how the data works and the link between input and output at the completion of the training. This solution is then applied to the test database, which is studied in the same way as the training database. This means that supervised machine learning skills will keep on improving by discovering new trends and associations as you train on new data.

Supervised learning itself is divided into two subtypes:

a. Classification

It is a supervised learning algorithm which learns from the input training data or observations and then it classifies the new observations into various classes or groups or categories. It is mostly used in prediction of the output for categorical data.

Example:

In medical imaging, for predicting whether the patient is having breast cancer or not, the breast thermograms of the patient are processed to extract features and textures from left and right breast and first classify them as normal or abnormal and further classifying abnormal as malignant or benign . Classification algorithms like K-nearest neighbor algorithms and Support Vector Machines are used for classification of the images.

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There are two types of classifiers:

i. Binary Classifier

If the classification problem has only two classes, then it is known as Binary Classifier.
Example: For predicting if a patient is having a disease or not, there can be two possible outcomes:

Yes(if having a disease) and
No(if not having a disease)

ii. Multi-class Classifier

If a classification problem has more than two classes, then it is known as Multi-class Classifier.
Example: In multi-class disease classification of brain MRIs, the images can be classified as normal, Alzheimer, AIDS, Cerebral Calcinosis, Metastaic or Glioma.

b. Regression

It allows us to predict a continuous output variable (y) which is dependent on one or more than one predictor variables(say x or x1,x2,....and so on).

Example:
If systolic blood pressure of a person is to be predicted, then it depends on two factors i.e. stress and sodium intake of the person. Here,
Continuous/real value of output variable (y)= systolic blood pressure
Predictor variables:

x1= stress
x2=sodium intake

The two major types of regression are linear regression and logistic regression.

i. Linear Regression

It quantifies the linear relationship between the dependent variable and the independent variable. If there is only one independent variable then it is called as simple linear regression. And if there is more than one independent variable then it is termed as multiple linear regression.

Example:
A Linear regression model can be used to predict medical charges based on insurance data.

ii. Logistic Regression

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It generates a probability i.e. a value that lies between 0 and 1, exclusive. The probability of the outcome is a dependent variable and different parameters by which the outcome is affected are the independent variables.

Example:

Logistic regression model can be used to predict health conditions in children that have cerebral palsy.

2. **Unsupervised Learning:** Because there are no labels to work with in unsupervised learning, hidden structures emerge. This is what makes unsupervised learning so adaptable. A large amount of data would be provided to the algorithms. It can then learn to group, cluster, and/or arrange the data in such a manner that humans (or intelligent computers) can interpret the newly arranged data. The algorithm understands the connections between data points without the need for human intervention.

Unsupervised learning algorithms may quickly adapt to the data by dynamically updating hidden structures, rather than a predetermined and fixed problem statement. More post-deployment options are available here than with supervised learning algorithms.

Unsupervised learning is further divided into two subtypes:

a. Clustering: A clustering problem is where you want to discover the inherent groupings in the data, such as grouping those people that are diagnosed with a disease based on its symptoms.
b. Association: An association rule learning problem is where you want to discover the rules that describe large portions of your data.

Example: Combination of low-level features that are automatically extracted from images and high-level knowledge from specialists to detect patterns.

3. **Reinforcement Learning:** Reinforcement learning is based on how people learn from facts in their daily lives. It introduces a self-improvement algorithm and uses the trial-and-error approach to learn new scenarios. Positive results are rewarded or 'encouraged,' while negative results are discouraged or 'punished.'

Example:

a. Reinforcement Learning System for encouraging Physical Activity in Diabetes Patients.
b. Reinforcement Learning can be used for Personalized Glycemic Control in Septic Patients.

The need for machine learning is simple, it can detect patterns and solve complex problems that we humans cannot. Machine Learning algorithms can do this tirelessly, consistently, and efficiently.

Some of the applications of machine learning in healthcare include:

- Handling administrative tasks with natural language processing.
- Tools for risk identification.
- Accelerating Medical Research.
- Diagnosis and disease identification.

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- Medical imaging diagnostics.
- Personalized medicine.
- Discovering new drugs with unsupervised learning.
- Smart health records.
- Research and clinical trials.
- Data crowdsourcing.
- Outbreak prediction.

In the past few years, the advancement in this field has made it possible for the machines to perform tasks that were deemed undoable for the machines. This shows that machine learning can be an important tool in medical imaging and diagnosis.

Machine Learning can be applied to medical imaging like X-Rays, CT-Scans, Thermography, and various other medical scans. The procedure is to identify patterns by training the machine learning model with the already available medical images. The top wellness and healthcare institutions all around the world are adopting Applied Intelligence for medical imaging to increase the speed and accuracy of images, monitor data in real-time, and eliminate the need for humans to do tedious and complex tasks. This has been enabling doctors to improve their approach towards treatments, speed of care, and related health conditions.

Preprocessing Techniques

The main objective of image pre-processing is improving information about the image that suppresses unnecessary distortions, enhances image features essential for further processing, and defines the object system.

An object is an entity (can be rigid, deformable, static, dynamic, physical, or conceptual) that is imaged and studied. An object system is a collection of such objects.

1. **CAVA (Computer-Aided Visualization and Analysis):** The science of computer-assisted imaging techniques, analysis, and visualization to facilitate new clinical research, training, education, and therapeutic strategies.
2. **CAD (Computer-Aided Diagnosis):** The science of computer-assisted imaging techniques and analyzing of diseases for diagnosis with the help of images.

Figure 11 shows how CAVA and CAD work.

Figure 11. Working of CAVA and CAD



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The Need for Image Pre-Processing

Pre-processing is needed for cleaning the image information for model input and is more suitable for further processing in CAD systems. Image preprocessing is advantageous as it helps in enhancing the quality of images and removing noise from images. If the input images are large in size, reducing the size of these images will significantly improve the model training time without reducing the model's overall accuracy. To reduce the size of an input image following aspects are taken into consideration:

- **The Volume of Interest (VOI):** to reduce data for speeding up CAVA operations.
- **The Region of Interest (ROI):** To specify a subset of the image domain.
- **The Intensity of Interest (IOI):** To specify a subset of the image intensities.

Pixel Brightness Transformation Techniques

The brightness of a pixel is changed by brightness transformations and this transformation is dependent on the characteristics of the pixel. The output value of a pixel depends on the corresponding input value of the pixel in pixel brightness transformation. Examples of such types of operators include; brightness, contrast adjustment, color correction, and transformations.

There are two different types of pixel brightness transformations:

1. **Position-dependent brightness correction:** The position-dependent brightness correction alters the brightness of pixels by taking into account the pixel's original brightness as well as its location in the image.
2. **Gray Scale Transformations:** The transformation is not dependent on the position of the pixel.
   a. Linear transformation

Linear transformation is divided into, identity transformation and negative transformation.

i. Identity transformation

In identity transformation, the pixels of the original image are directly mapped to the output image. The output image and the input image are the same, hence it is called identity transformation.

ii. Negative Transformation

Assuming there are [L-1] grey levels, i.e. from 0 to [L-1], Negative transformation can be achieved by subtracting the value of all pixels by [L-1] and then mapping the pixels. For instance, in an 8-bit grayscale image, there are 256 grey levels. If the value of the pixel under consideration is 10, using the formula:

new intensity of pixel = [L-1] - intensity of the pixel
we get (256 - 1 - 10) = 245. 245 will be the intensity of that pixel in the output image.

The darker pixels become lighter and lighter pixels become darker.

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b. Logarithmic Transformation

Logarithmic Transformation is used to reduce the contrast of brighter regions.
New intensity of pixel = C x log(1+ intensity of the pixel)
C is a constant, as the value of C increases the brightness of the image also increases. Here, 1 is added to the value of each pixel because if the value of any pixel is zero, then log(0)= infinity.

c. Power Transformation

Power Transformation is used to enhance the contrast of brighter regions. New intensity of pixel = C x (intensity of the pixdel)^{y}
For the different levels of 'y', various levels of enhancement of the image are obtained.

Geometric Transformation Techniques

Geometric transformation technique is used for removing the geometric distortion from the image which is present when the image is captured. The geometric transformation has two basic techniques

1. **Spatial transformation or Pixel coordinate transformation:** In this transformation technique, one coordinate system of the image is mapped with other coordinate systems.

Two types of mapping can be done forward mapping and inverse mapping.

a. Simple Mapping Techniques
   i. Translation

Moving the image from one position to another is known as translation.

   ii. Scaling

Scaling is used for resizing the image i.e. stretching (zoom in) or contracting(zoom out) the image.

$$\left(x'y'\right) = \left(s_x 00 s_y\right).\ (x,\ y)$$

Sx > 1 image is going to stretch
Sx = 1 image will remain same
Sx < 1 image will contract

   iii. Rotation

This is used to change the image orientation by an angle θ.

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$$x' = x.coscos(\theta) - y.sinsin(\theta)$$

$$y' = x.sinsin(\theta) + y.coscos(\theta)$$

$$(x'y') = (coscos(\theta) - sinsin(\theta)sinsin(\theta)coscos(\theta)) . (xy)$$

iv. Shearing

Image can be sheared in both the direction i.e. horizontal and vertical. Both horizontally and vertically pixels are relocated by a distance that increases linearly.

$x' = x + \text{Shx} .y$

$y' = y + \text{Shy} . x$

OR

$$(x'y') = (1Sh_x Sh_y 1).(xy)$$

b. Affine Mapping

This is a linear mapping technique. It conserves all the points, straight lines, and planes. Most of the simple mapping techniques are special cases of affine mapping.

c. Non-linear mapping

i. Twirl

Colors of images are twirled at position (x, y) instead of distance (x¢, y¢). Rotate the image by an angle of θ with the centre as (xc, yc). This progressively turns the image at a spiral distance S which increases up to Smax from the centre. Outside of the radial distance Smax the image remains unaffected.

ii. Spherical

In this technique, the image gets zoomed in at the centre.

Dx = x' - xc

Dy = y' – yc

S =

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Z =

x = x' -

y = y' -

Where, (xc, yc) - center of the lens
Lmax - radius of the lens
τ - refraction index

Filtering Techniques

Filtering is the transformation or enhancement of a picture. You can, for example, apply a filter to an image to highlight some elements while removing others. The main functionalities of image processing by filtering include sharpening, edge enhancement, correcting background variations, suppressing random noise, and smoothening.

1. **Spatial Filters:** In spatial filtering, the pixel which is going to be processed, its values not only depend on itself but also the value of the neighboring pixels. Therefore, the value of the current pixel is calculated by applying an algorithm that affects neighboring pixels also.

Different types of spatial filters are as follows:

a. Liner Filter (convolution)

The outcome of the linear filtering is equal to the sum of products of the mask coefficients with the equivalent pixels exactly beneath the mask.

= [M(-1, 1)*I(x-1, y+1)]

+[M(0, 1)*I(x, y+1)]+[M(1, 1)*I(x+1, y+1)]

+[M(-1, 0)*I(x-1, y)]+[M(0, 0)*I(x, y)]

+[M(1, 0)*I(x+1, y)]+[M(-1, -1)*I(x-1, y-1)]

+[M(0, -1)*I(x, y-1)]+[M(1, -1)*I(x+1, y-1)]

b. Non-Linear Filter

Nonlinear filtering depends conditionally on the neighboring pixels' values of a relative pixel.

c. Smoothing Filter

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A smoothing filter is used for reducing or removing the noise present in the image and for blurring purposes. Blurring is used for removing unwanted information present in the image before feature extraction and to connect small breaks in curves and lines. Smoothing filter is also known as a Median filter. Salt and pepper noise can be removed by using the median method.

Smoothing spatial filters are of two types

i. Order Static Filter

An Ordered static filter is basically a non-linear filter. The value of the center pixel is replaced by the value of neighboring pixels calculated using ranking result ordering.

ii. Smoothing Linear Filter

Smoothing linear filters basically means the values of the neighborhood pixel of the filter mask. As a result, it is also known as "mean filter" or "averaging filter"

d. Sharpening Filter

The main aim of using these filters is to highlight the blurred detail and enhance the fine details. Sharpening of the image can be done by spatial partial derivation.

For a digital image I(x, y)

$$\frac{\partial I}{\partial x} = I\left(x+1, y\right) - I\left(x, y\right)$$

$$\frac{\partial I}{\partial x} = I\left(x+1, y\right) - I\left(x, y\right)$$

2. **Frequency Filters:** Processing of images in the frequency domain is done using frequency filters. By using the Fourier Transformation function, images are converted to the frequency domain. When frequency domain processing is completed, the image gets transformed back into the spatial domain by inverse Fourier transform. An image can be converted into a smoother one by minimizing high frequencies in the spatial domain whereas minimizing the low frequencies highlights the image's edges.

Different types of frequency filters are:

a. Low Pass Filters

The "low pass filter" is the simplest fundamental filtering process. A blurring or smoothing filter, often known as a low pass filter, averages out rapid fluctuations in intensity. It accomplishes this by computing the average of a pixel's eight neighbors and the pixel itself. The result then takes the place of the previous value. For each picture in the pixel, this procedure is repeated.

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Low pass filter is of three types:

i. Ideal Low Pass Filter

The ideal low pass filter eliminates the high-frequency components of Fourier transform that exceed the specified cut off frequency F0. The transfer function of the ideal low pass filter is:

$$P(u,v) = \{1 \; if \; F(u,v) \le F_0 \quad 0 \; if \; F(u,v) > F_0$$

ii. Butterworth Low Pass Filter (BLP)

In the chosen pass band of order d, the Butterworth low pass filter is used to eliminate high-frequency noise with little loss of picture data. The Butterworth low pass filter of order d with cutoff frequency F0 has the following transfer function:

$$P(u,v) = \frac{1}{1+\left[F(u,v)/F_0\right]^{2d}}$$

iii. Gaussian Low Pass Filter

The major advantage of using a Gaussian low pass filter is that it not only connects broken text but also reduces blemishes in an image. It also removes noise from an image. Using Gaussian low pass filter the brightness of images is not preserved. Its Transfer function is defined as:

$$P(u,v) = e^{-F^2(u,v)/2\sigma^2}$$

Here, σ =standard deviation of the distribution.

If σ (standard deviation) is replaced with F0 where F0 is the cut-off radius, then the transfer function of the Gaussian low pass filter is defined as:

$$P(u,v) = e^{-F^2(u,v)/2F_0^2}$$

b. High Pass Filters

As the name implies, these filters only allow high frequencies to pass while rejecting frequencies below the cut-off frequency. To make the image seem sharper, a high pass filter might be utilized. These filters draw attention to the image's borders and tiny features. High pass filters are the polar opposite of low pass filters,

$$HPF = 1 - LPF$$

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High pass filter is of three types:

i. Ideal high pass filter

The transfer function of an ideal High Pass Filter is defined as:

$$P(u,v) = \{0 \; if \; F(u,v) \le F_0 \;\; 1 \; if \; F(u,v) > F_0$$

ii. Butterworth high pass filter:

The transfer function of butter worth high pass filter can be expressed as

$$P(u,v) = \frac{1}{1+\left[F_0 / F(u,v)\right]^{2n}}$$

where p = the order and F0= cut-off frequency /the cut- off radius

iii. Gaussian high pass filter

The transfer function of the Gaussian high pass filter can be defined as:

$$P(u,v) = 1\text{-}\, e^{-F^2(u,v)/2F_0^2}$$

c. Band Pass Filters

A band pass filters very high and extremely low frequencies while preserving a middle-range band. Band pass filtering may be used to enhance the edges (by suppressing low frequencies) while lowering noise (by suppressing high frequencies) at the same time. In the frequency domain, a band pass filter function is generated by multiplying the low pass filter function with the high pass filter function, where the high pass's cutoff frequency is lower than that of the low pass. As a result, if the low-pass filter function is present, a band pass filter function can theoretically be achieved.

d. Band Reject Filters

A band-reject filter (also known as a band-stop filter) is the reverse of the band pass filter. It suppresses frequencies that lie within the range of a higher and lower cutoff frequency.

Various types of band-reject filters are:

i. Ideal band-reject
ii. Butterworth band-reject
iii. Gaussian band-reject filter

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Segmentation Techniques

The technique of highlighting or separating a portion of a picture is known as image segmentation. It's usually used to locate crucial areas of a picture or a specific object of interest. Some types of segmentations are listed below:

1. **Thresholding:** The process of transforming a grayscale image to a binary picture is known as thresholding (image with only two-pixel intensities, 0 black, and 1 white). It is used to separate the background from the foreground. If the value of a pixel in a picture exceeds a particular specified threshold, it undergoes some transformation, and if the value of the pixel is less than the threshold, it experiences the other transformations. There are two sorts of thresholds: global and local. A single threshold value is chosen for the whole picture in global thresholding. When the lighting in a picture is not consistent, local thresholding divides the picture into sub-images with each sub-image having a distinct threshold.
   a. Histogram Shape-Based Thresholding

The histogram method assumes that there is an average value of the background and foreground, but in reality, there is some deviation from these average values. One iterative method is used to calculate the threshold (T) because it is robust and simple.

Step 1: An initial threshold (T) is selected arbitrarily by any other desired method.
Step 2: The image I(x, y) is segmented into the foreground or object pixels and background pixels:
Object pixels *(OP){ I(x, y): I (x,y) T }*
Background pixels *(BP){ I(x, y): I (x,y) < T }*
Step 3: The average of each pixel set is calculated.
AOP ← Average of *OP*
ABP ← Average of *BP*
Step 4: A new threshold is formed, which is the average of AOP and ABP:
Tnew(AOP+ AbP)2
Step 5: In step 2, use the new threshold obtained in step 4. Repeat till the new threshold matches the one before it.

Once we get the threshold, the value of each pixel is compared with it and we get the segmented image.

   b. Clustering-Based Thresholding (K-means Thresholding Method)

The unsupervised K-Means clustering technique is used to separate the ROI from the background. Based on the K-centroids, it clusters or partitions the provided data into K-clusters or sections. When the data is unlabeled (i.e. data without defined categories or groups), this method is applied.

Step1: Specify the number of clusters K.
Step2: Place the centroids randomly.
Calculate the sum of the squared distance between data points and all K centroids.
Step3: Each data point should be assigned to the cluster that it is the closest to.

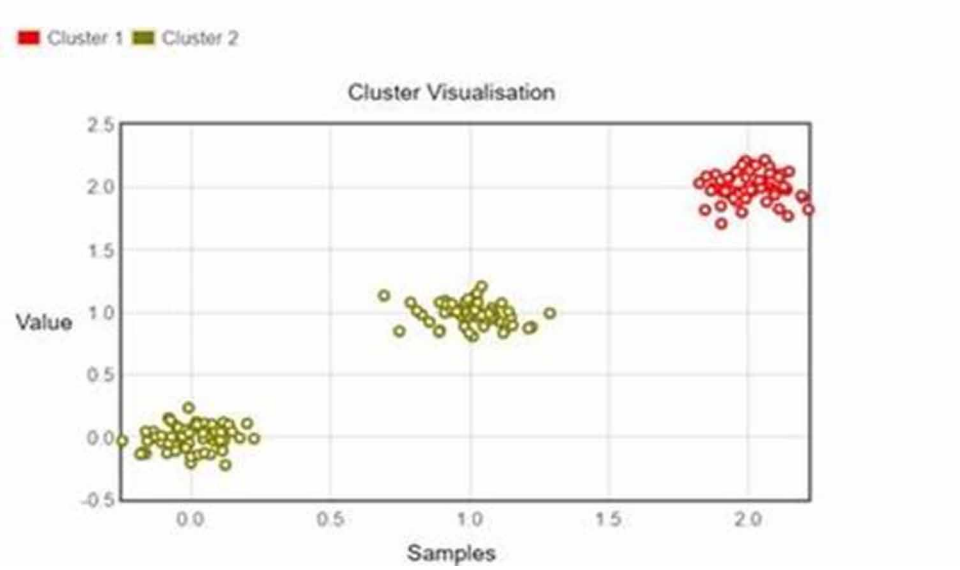
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Step4: The new centroids for clusters are calculated by taking the average of all data points belonging to each cluster.

Step5: Continue iterating until the centroids do not change, or set a threshold and stop iterating if the change in centroid is less than that threshold.

Figure 12 shows the final output of an example with K=2.

Figure 12. K-Means algorithm



For an RGB image, if there are K clusters then the image will be segmented into K colors.

2. **Edge-Based Segmentation:** Edge detection is an important area for medical diagnosis. Edge detection is basically the change in grey tones in a neuro image, edges are local variations in intensity. Edge segmentation makes a border around the important section of an image, only this part can be processed further reducing the amount of data and simultaneously increasing the speed.

Commonly used edge detectors are:

a. Roberts Edge Detector
b. Sobel Edge Detector
c. Prewitt Edge Detector
d. Kirsch Edge Detector
e. Robinson Edge Detector
f. Canny Edge Detector
g. Laplacian of Gaussian (LoG) Edge Detector
h. Marr-Hildreth Edge Detection

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3. **Region-Based Segmentation:** Region-based segmentation divides an image into segments by grouping pixels with similar attributes such as intensity, pattern, or form. (Dogra, 2018).

It can be divided into two main categories:

a. Region Growing and Merging: It starts with a single seed pixel, which is then merged with pixels that have similar properties.
b. Region Splitting: It is the opposite of merging, in splitting the whole image is considered which is then split into sub regions until a uniform sub region is found.

Morphology Techniques

1. **Binary Morphology**: Binary images have many flaws. Binary images created using a simple thresholding technique contain noise in it. To remove these noises and other imperfections morphological image processing is used.
   a. Erosion

Erosion operation is applied between a structure and a binary image result in the formation of the new image. The first image is always the one that has to be eroded and the structure part is a small set of coordinate points (Fisher, Perkins, Walker, & Wolfart, Erosion, n.d.).

b. Dilation

In dilation, the boundaries of the image are enlarged gradually. Hence the size of foreground pixels increases while the size of holes in the region decreases. Thus, dilation is just the opposite of erosion (Fisher, Perkins, Walker, & Wolfart, Dilation, n.d.).

c. Opening

After performing the opening technique the resulted image that we get is equivalent to performing erosion and then dilation (Fisher, Perkins, Walker, & Wolfart, Opening, n.d.).

d. Closing

After performing the closing technique the resulted image that we get is equivalent to performing dilation and then erosion (Fisher, Perkins, Walker, & Wolfart, Closing, n.d.).

e. Hit and Miss

Hit and miss is an advanced version of the erosion and dilation technique. Erosion and dilation contains only foreground pixel whereas in hit and miss both foreground and background pixels are visible (Fisher, Perkins, Walker, & Wolfart, Hit-and-Miss Transform, n.d.).

f. Thinning

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This technique is somewhat similar to erosion or opening. It is used for eliminating selected foreground pixels. Vast application of this is seen in skeletonization (Fisher, Perkins, Walker, & Wolfart, Thinning, n.d.).

g. Thickening

This technique is somewhat similar to dilation or closing. It is used for growing selected foreground pixels. This technique is majorly used for determining the convex hull of the shape (Fisher, Perkins, Walker, & Wolfart, Thickening, n.d.).

2. **Grayscale morphology**: Grayscale morphology is a simplification of multidimensional binary morphology i.e. of 1bpp image. In this morphological technique instead of OR and AND operation Min and Max operation are used respectively
   a. Erosion

Used for a grayscale image where light details of an image are reduced and the image becomes dark.

b. Dilation

In this technique maximum grayscale region is considered for the entire region. Dark details are reduced and images become brighter.

c. Opening

This technique is used for reducing bright details. After applying this technique to an image result into the preservation of foreground region which is similar in shape to its structure element

d. Closing

This technique is used for the reduction of dark details. After applying this technique, an image can contain complete structure elements while all the background pixels are rejected/removed.

Machine Learning Algorithms

1. **Support Vector Machine (SVM):** SVM stands for Support Vector Machine and is a Supervised Learning method that may be used to solve both classification and regression issues. The Support Vector Machine algorithm's main goal is to find the best-fitting line or decision boundary that can divide the n-dimensional space into classes, allowing the addition of new data points to the proper category in the future. This best fitting line or decision boundary is called a hyperplane (Bora, 2020). The resulting hyperplane will be dependent on extreme points (i.e. the points that are closest to the hyperplane) or border training patterns called support vectors. The hyperplane is always produced by maximising the margin which means there should be maximum distance between the data points.

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Example:

a. SVM can perform bacterial classification by using the features that are extracted from the bacterial images. Thus, for effective and preventative treatment of a person this bacterial type diagnosis can be performed as it helps in characterization of diseases.
b. By feeding the extracted texture characteristics of thermographic breast pictures to the Support Vector Machine, an SVM classifier may be utilized to automatically classify normal and malignant breast states.

Pattern matching and classification, function approximation, data clustering, and forecasting are just a few of the practical challenges for which SVM is utilized. SVM offers a high classification accuracy, strong fault-tolerance capabilities, and helps to reduce model risk factors. (Bora, 2020).

2. **Naïve Bayes:** Bayes' theorem is also called Bayes Law or Bayes Rule, which determines the probability of a hypothesis having prior knowledge. The formula for Bayes' theorem is given as:

$P(B) = P(B/A) * P(A)/P(B)$

Where,

$P(B)$ = Posterior probability
$P(B/A)$ =Likelihood probability
$P(A)$ = Prior Probability
$P(B)$ = Marginal Probability

Naïve Bayes Classifier Algorithm

a. The supervised learning technique known as the Nave Bayes algorithm is based on the Bayes theorem and may be used to solve classification issues.
b. The Nave Bayes Classifier aids in the development of rapid machine learning models capable of making quick predictions.
c. It's a probabilistic classifier, which means it makes predictions based on the likelihood of an item.
d. In Naïve Bayes Classifier there is no inter-dependency between the different feature variables. Hence, they are termed as conditionally independent which is the definition of 'naive'.

Naïve Bayes Classifier is very useful in predicting diseases and it can help physicians for a better diagnosis.

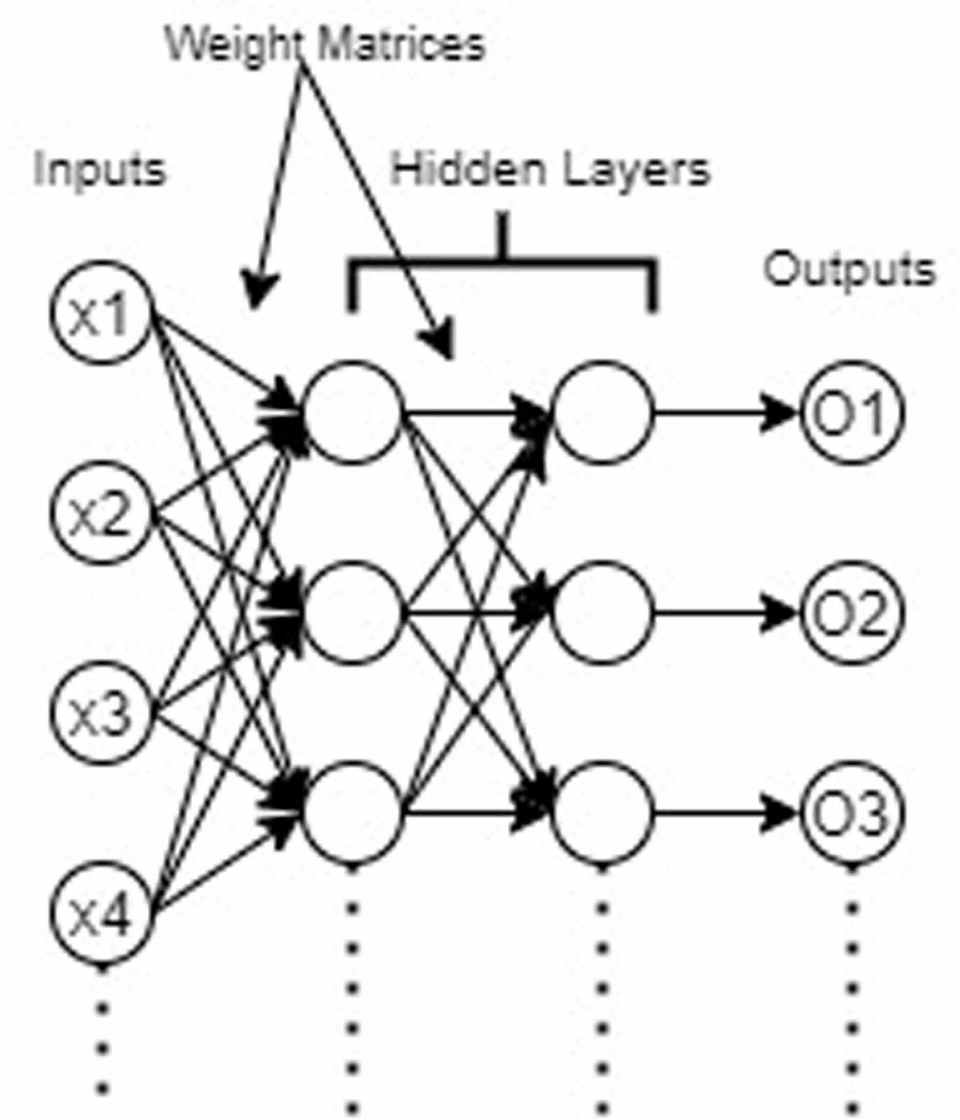
Example:

a. Using Naïve Bayes Classifier for brain disease prediction.
b. Using Naïve Bayes predictor in cancer diseases.

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3. **Neural Networks**: Artificial Neural Networks (ANNs) are a powerful tool to make diagnosis efficient. ANN is a collection of interconnected processing elements called neurons. These neurons are interconnected extensively as shown in Figure 13. They can make sense of complicated data. A layer is a small collection of neurons, with the input layer being the first and the output layer being the last. There are some hidden layers between the input and output layers.. Neural networks are ideal for diagnosing diseases from scans as they don't need to be trained specifically for each and every scan. By altering the connections between layers, they may learn by example and be trained to do a specific task.

Figure 13. Neural Networks



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4. **Deep Learning:** Deep learning, sometimes referred to as deep neural networks, is a type of neural network that has more dense hidden layers. Generally neural networks have less than 5 layers but, deep neural networks typically have more than 20. This is possible because of availability of more computational power. Convolutional Neural Networks (CNN) is most commonly applied to images. It's a deep learning method that can accept input photos, apply weights to items in the image, and distinguish one image from other.
5. **Decision Trees:** Decision tree is the most commonly used machine learning algorithm which comes under the category of supervised learning. Their use increases due to interpretation of rules which are straightforward which help us to understand the data provided more accurately and making/taking a good decision. Node-link diagrams are the most common visualization technique for tree. They provide the best data split possible. Scatter Plot or histogram, box plot and dot plot are additional visualization techniques that are used along with tree visualization. KL Divergence may be used to identify all of the key characteristics as well as analyse the decision tree and other hidden data correlations.

Steps in Developing Machine Learning Applications

There are seven steps in the development of a machine learning applications production cycle.

Step 1: Problem Description

The first step towards developing any set of requirements for building any model is understanding what the problem exactly is and on the basis of that, you can select the type of data required.

Step 2: Finding and choosing the correct dataset

Once we know what we want, then we can move to the next step, data collection. It lays the foundation of the project; the quality of data determines how good the model will turn out. Data can be collected from surveys, web scraping, trusted institutions of the selected domain, etc.

Step 3: Data Preparation

After we have the data we need, we have to make sure that it is in a usable format. The data should be in a randomized order as we don't want the order of data to affect its predictions. We fill or discard all the empty rows. We also split the data into training and testing sets in this step. Generally, the ratio of training data to testing data is in the range of 7:3 or 8:2.

Step 4: Selecting a suitable Machine Learning algorithm

In this step, we select the appropriate algorithm. Some algorithms perform better for a dataset of images but not for numerical data, so selecting the correct algorithms can improve the accuracy of the model.

Step 5: Model Training and testing

Training data is the data that is used to incrementally enhance the ability of a machine learning model to predict the result you design your model to predict. The training process involves the initialization of some arbitrary values for say X and Y of our model, predicting the output with those values, then comparing it with the model's prediction and adjusting the values to match previous predictions. Test data is used to measure the performance factors such as precision or efficiency, of the algorithm that you are using to train the machine. Test data will help you understand how your model can predict new responses, depending on its training. Both training and test data are essential for enhancing and validating various machine learning models.

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Step 6: Fine-tuning of model

If not satisfied with the accuracy, we can improve it by tuning some parameters in the data set. It may include removing some columns that are not important, adding columns that were thought to be unimportant but are. This step can be very exhaustive but can help to increase the accuracy significantly.

Step 7: Deployment of model

The final step is deploying the model, it is done once we have achieved the desired accuracy.

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Chapter 5
Applied Intelligence for Mental Health Detection:
ManoVaidya – A Mental Health Therapist

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ABSTRACT

Mental health is a major healthcare issue around the world, and it must be made a priority in the healthcare sector. That being said, it seems that progress in this area is moving at a slow rate. These conditions aren't always difficult to live with, but they also put you at risk for heart failure, severe anxiety, and depression, leading to serious stress and physical disability. In middle and upper nations, a majority of people deal with at least one of these psychiatric disorders at a certain stage in their lives. Artificial intelligence techniques have recently received a lot of attention in a variety of areas, including psychological health. A personalized therapy that aims to deliver emotional support to a particular person has to be enabled with the help of specialized artificial intelligence methods and ML algorithms. The aim of this chapter is to evaluate and create a system that assists a person in predicting and curing his or her psychiatric disorder using various artificial intelligence concepts and strategies, thus assisting people in curing their problems.

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INTRODUCTION

In India, mental diseases are on the rise. This occurrence has resulted in a vast volume of mental health information. It could turn out to be useful. The knowledge gained by the use of a data mining algorithms can help to predict mental illness. India is a country where data from the healthcare sector is undervalued. A person's general physical, psychological, and community well-being is primarily determined by their mental health, but there are fifteen million people suffering from a psychiatric illness which is a sector of concern. The authors aim to develop ManoVaidya as an application that will assist Indians in detecting and resolving mental health issues. Psychological health is critical to our intellectual and physical capacity to learn, emote, communicate with others, contribute to society, and maximise productivity. On this basis, mental health development, prevention, and recovery should be considered a critical issue for people, families, and cultures all around the world. Truth, on the other hand, tells a different story. Depression, personality disorders, and psychiatric disabilities impacts individuals all over the world.

BACKGROUND

The researchers studied and understood a variety of papers and reviews to assess the role of a machine learning in the diagnosis of mental illness in individuals of various ages. Many studies have focused to diagnose mental disease among the younger generation. Various methods and strategies for evaluating and conducting machine learning are depicted in other studies and publications.

The researchers have summarized the research in the Table 1, 2 & 3 given below.

Table 1. Summary of Literature survey

Citation	(Khattar et al., 2020)	(Avasthi et al., 2013)	(Resom et al., 2019)
Inference	To detect mental condition of young Indian students in the pandemic a survey was conducted, and the collected data was visualized, and it was found out that 42.9% of them were feeling frustrated, anxious, depressed, bored and overworked.	Yoga and Meditation are useful in Psychotherapy.	Different algorithms used for the depression detection and generation of Questionnaire.
Methods	Apriori algorithm was used to find association rules.	Yoga & Meditation to help reduce stress and anxiety.	Using features like Text-based, audio, social media and detection can be conducted.

Table 2. Summary of Literature Survey

Citation	(Khan et al., 2018)	(Mody & Mody, 2019)
Inference	Cross-validation performance of the algorithms & data mining for mental healthcare.	By reviewing algorithms and thresholds, we will develop different mental health programs, such as interactive counselling and diagnostic systems.
Methods	Planning & Background Analysis, Data acquisition, Data pre-processing and implementation of data mining	Combination of above-mentioned system and personalized mental care methods.

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Table 3. Summary of Literature Survey

Citation	(Liu et al., 2019)	(Lovejoy, 2019)
Inference	A brief overview of the method of diagnosing psychiatric disorders, as well as an examination of the major data types created and the role of AI in diagnosis and its application performance.	AI integration of healthcare could increase treatment quality. Monitoring and treatment can help patients to ensure the successful implementation of new technology in mental health.
Methods	AI-based applications of MRI, EEG and kinesics diagnosis along with the use of AI algorithms such as the Bayesian model, Logic Regression, Support Vector Machines and deep learning.	The new technology consists of diagnostic tools, monitoring, chatbot and treatment to improve mental health.

MAIN FOCUS OF THE CHAPTER

Our mutual and human capacity to think, sound, communicate, live and enjoy lives depends on our mental health and well-being. Support, security and rehabilitation of mental health should also be viewed as a critical concern for people, families and cultures worldwide. The truth today, however, is very different. Depression, personality disorders, and psychiatric disabilities affect people all over the world.

The main focus of this chapter is to develop a system that would help an individual to detect and overcome his/her mental health condition using different techniques and methods of artificial intelligence, thereby contributing in helping people to heal their condition. The focus is to use ancient Indian techniques to cure mental health.

The worldwide wellbeing report shows how mental disease is the world's leading cause of disability and poor health. About 450 million people suffer from a mental health condition. Depression, which is very normal but often very serious, affects the way a person thinks, the type of feelings he or she has and how he or she responds. It induces depression and a lack of interest in previously loved activities. It impairs a person's capacity to focus on jobs, research, and everyday chores. In a given year, one out of every 15 people suffers from depression, demonstrating the severity of the disease. In a culture where, due to social isolation and shame, people are already reluctant to address their mental health conditions.

Furthermore, the major percent of the time, people suffer from those diseases, but are unaware of it because they are unable to identify the signs. Many individuals may not have access to mental health services, even those that do have access are also unable to seek mental health care. Since they are reluctant to pursue mental health treatment, they never know that they have those conditions and therefore go untreated. About 5% of humans are so seriously impaired by psychiatric illnesses that their capacity to participate in culture is jeopardized.

Researchers suggest a method that will use machine learning algorithms to identify a person's level of depression. It will aid in determining the seriousness of the condition of the patient.

ISSUES, CONTROVERSIES, PROBLEMS

Depression detection

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1. The dilemma was that Keras's latest python implementation did not fit well, so there was no way of training with the same version of the model. The problem is resolved by using the older edition of Keras.
2. The error in use of neural network algorithm was the compatibility issue with the existing python production environment. So, the solution was developed using random forest algorithm and accurate results were achieved.

SOLUTIONS AND RECOMMENDATIONS

ManoVaidya - is an application where people know about their mental health status and also help them to overcome their mental health conditions. The main objective of this project is to develop a system which can predict a person's mental state and help overcome the negative state of mind by using artificial intelligence techniques. The application includes features such as the cognitive health test, AI chatbot, anonymous therapy chatroom and self-care activities. The product will be designed using bottom-up object-oriented design approach. All the separate modules will be generated first and then these subsystems will be integrated to form our main system. The flowchart of ManoVaidya is shown in Figure 2. The flowchart explains the working of the proposed application to understand the flow efficiently.

The researchers created the survey using the recommendation provided by Dr. Shrirang Joshi, who is their campus counsellor. The survey form questions are based on factors leading to ill mental health like psychology, sociology, physiology.

Figure 1 depicts the dataset collected from the survey. In figure 1, the dataset has answers like "Not at all", "Some of the Days", "Several Days", "Nearly Every day" to the following questions given below.

The questions formatted for survey form are:

1. What is your age range?
2. Your gender?
3. What is your occupational status?
4. How often do you have little interest or pleasure in doing things?
5. How often do you feel down, depressed, or hopeless?
6. How often do you feel tired or feel having very little energy?
7. How often do you feel bad about yourself - or that you are a failure and you have let yourself or your family down or have felt any sort of guilt?
8. How often do you feel trouble concentrating on things, such as reading the newspaper or watching television?
9. How often do you feel that you are moving or speaking so slowly that other people could have noticed or the opposite -being so fidgety or restless that you have been moving around a lot more than usual?
10. How often do you feel sad or like crying?
11. How often do you feel angry?
12. How often do you experience having confusion or slowed thinking?
13. How often do you experience having thoughts that you would be better off dead, or of hurting yourself?
14. How often do you overeat or have a poor appetite?

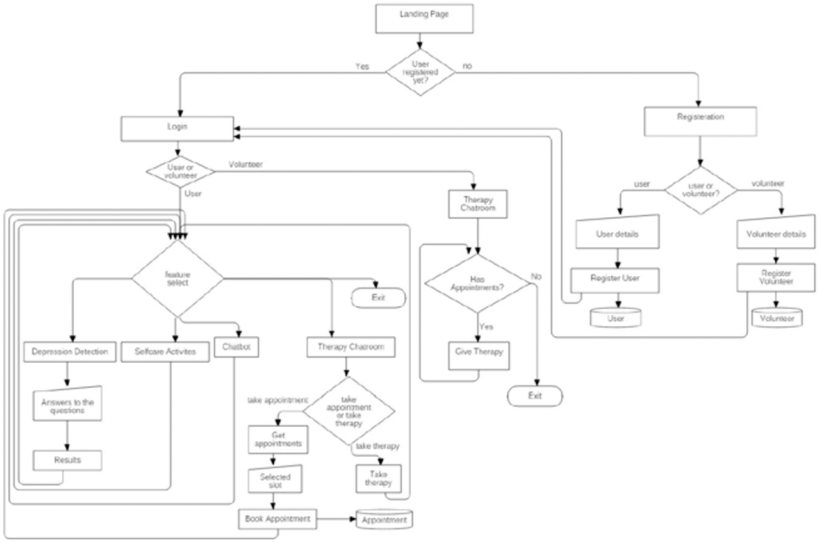
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15. Is your sleep cycle disturbed or irregular?
16. Have you ever been diagnosed with a mental disorder before?

Figure 1. Dataset collected from Google survey

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	Timestar	age	gender	occupation	interest_pleasure	depressed	feel_tired	feel_bad	feel_trouble	feel_restless	feel_sad	feel_angry	confusion	thoughts	poor_appetite	sleep_c
2	11/24/20	15-25	Male	Student	Some of the days	Some of the	Some of thi	Some of t	Some of the	Some of the di	Some of th	Not at all	Some of th	Not at all	Some of the da	Some of
3	11/24/20	15-25	Female	Student	Some of the days	Nearly Every	Several da	Nearly Ev	Several days	Some of the di	Several da	Several day	Several da	Several d	Some of the da	Several
4	11/24/20	15-25	Male	Student	Nearly Everyday	Not at all	Some of thi	Not at all	Some of the	Not at all	Some of th	Some of the	Some of th	Not at all	Some of the da	Not at a
5	11/24/20	15-25	Female	Student	Nearly Everyday	Nearly Every	Several da	Several di	Several days	Several days	Nearly Eve	Nearly Ever	Some of th	Nearly Ev	Some of the da	Some of
6	11/24/20	26-35	Female	Service	Nearly Everyday	Some of the	Some of thi	Not at all	Not at all	Not at all	Not at all	Some of the	Not at all	Not at all	Not at all	Not at a
7	11/24/20	15-25	Female	Student	Some of the days	Several days	Nearly Ever	Several di	Several days	Several days	Several da	Several day	Several da	Some of t	Several days	Nearly E
8	11/24/20	15-25	Male	Student	Several days	Several days	Several da	Not at all	Some of the	Some of the di	Some of th	Several day	Nearly Eve	Not at all	Not at all	Some of
9	11/24/20	15-25	Male	Student	Some of the days	Some of the	Several da	Not at all	Several days	Not at all	Several da	Several day	Nearly Eve	Not at all	Some of the da	Not at a
10	11/24/20	15-25	Male	Student	Some of the days	Some of the	Some of thi	Not at all	Some of the	Several days	Some of th	Several day	Several da	Not at all	Nearly Everyda	Several
11	11/24/20	15-25	Male	Student	Some of the days	Some of the	Some of thi	Some of t	Several days	Nearly Everyda	Some of th	Several day	Nearly Eve	Several d	Several days	Some of
12	11/24/20	36-45	Female	Other	Nearly Everyday	Some of the	Some of thi	Some of t	Some of the	Some of the di	Some of th	Some of the	Some of th	Some of t	Some of the da	Some of
13	11/24/20	26-35	Male	Service	Nearly Everyday	Some of the	Not at all	Not at all	Some of the	Some of the di	Not at all	Some of the	Some of th	Some of t	Some of the da	Not at a
14	11/24/20	36-45	Male	Businessmai	Several days	Some of the	Several da	Not at all	Some of the	Several days	Some of th	Some of the	Some of th	Some of t	Some of the da	Several
15	11/24/20	46-55	Female	Businessmai	Some of the days	Some of the	Not at all	Not at all	Not at all	Some of the di	Not at all	Some of the	Not at all	Not at all	Not at all	Some of
16	11/24/20	15-25	Male	Student	Several days	Not at all	Some of thi	Not at all	Some of the	Some of the di	Not at all	Some of the	Several da	Not at all	Some of the da	Some of
17	11/24/20	36-45	Female	Freelancer	Some of the days	Not at all	Some of thi	Not at all	Some of the	Not at all	Not at all	Some of the	Not at all	Not at all	Not at all	Not at a
18	11/24/20	15-25	Male	Student	Some of the days	Several days	Several da	Nearly Ev	Not at all	Some of the di	Some of th	Some of the	Several da	Not at all	Nearly Everyda	Some of
19	11/24/20	15-25	Male	Service	Some of the days	Several days	Several da	Several di	Not at all	Some of the di	Several da	Several day	Several da	Some of t	Some of the da	Several

Figure 2.



COGNITIVE HEALTH TEST: Data collected in the survey will be assessed to detect the mental health state of the user using the machine learning algorithm.

A machine learning model is to be trained on the dataset collected to detect the depression of the user on providing user inputs to questions asked in the test. The test will contain the questions framed by authors based on factors of mental health such as psychology, sociology, and physiology under the guidance of a professional psychiatrist. The result of the test is being calculated based on the user input and the result of the trained model. The obtained result will then be indicated on an indicator according to different categories of severity like “None”, “Mild”, “Moderate”, and “Severe”.

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THERAPY CHAT ROOM: The user will be able to have voice call conversations with a volunteer therapist to help and support them in recognizing and improving their mental health condition. A platform to have anonymous conversations with professional therapists will be provided wherein the user and therapist will be anonymous to each other. In recent times, it is seen that people experiencing mental disorders tend to keep their condition private and confidential so anonymity is being provided so that users can openly come and use this platform for their betterment.

SELF-CARE ACTIVITIES: Users can avail the various self-care techniques provided to help and monitor their mental state with the help of activities like yoga, meditation, inspirational stories and motivational routine. Yoga is very beneficial in treating mental illnesses and stress so many yoga asanas are being recommended with the graphical depiction of the pose in the system. Meditation may provide a deep state of relaxation and a peaceful mind, it also helps in decreasing negative emotions and improving imagination and creativity also increases patience and tolerance so to help while meditating meditational videos are being provided.

AI CHATBOT: With this functionality the user will be able to communicate and converse with a chatbot as a friend and the chatbot will be able to provide positive advice and give optimistic thoughts 24 by 7 to any user in need. The AI chatbot is trained on multiple datasets such as personalized dataset containing human conversations based on emotions, psychology, and humor, application oriented dataset and a counsellor recommended therapy conversation dataset.

The machine learning algorithm used is Random forest.

Random forest is one of the simplest and diversified classification and regression machine learning algorithm. It builds a “forest” from a group of decision-making trees that are usually formed using the technique of “bagging”. The common principle of the bagging approach is to maximize the total outcome by a mixture of learning models.

The output of depression detection is shown in figure 3. The output shows the level of depression detected in the individual who has taken the survey.

Steps used to predict depression of the user:

Step 1: The user will complete the survey form.
Step 2: The input from the user will be rendered to the machine learning model as input for prediction.
Step 3: For training the model the data will be cleaned, tested for any missing data and non-numeric columns
Step 4: Feature engineering will then be done on dataset wherein unnecessary features from the dataset will be removed.
Step 5: The data in remaining features will then be encoded.
Step 6: Then the dataset is used to train the model using Random Forest algorithm, dataset for training and testing data is split.
Step 7: The Machine learning model is created and trained using the randomizedsearchcv()
Step 8: The best parameters are calculated, building and fitting forest and make class predictions for the input test set.
Step 9: The average of predicted result and the actual result will be taken and based on that the result will be displayed and using that the indicator will show how much depressed the user is on a scale of categories like None, Mild, Moderate and Severe.

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Figure 3. Output of Cognitive Health Test

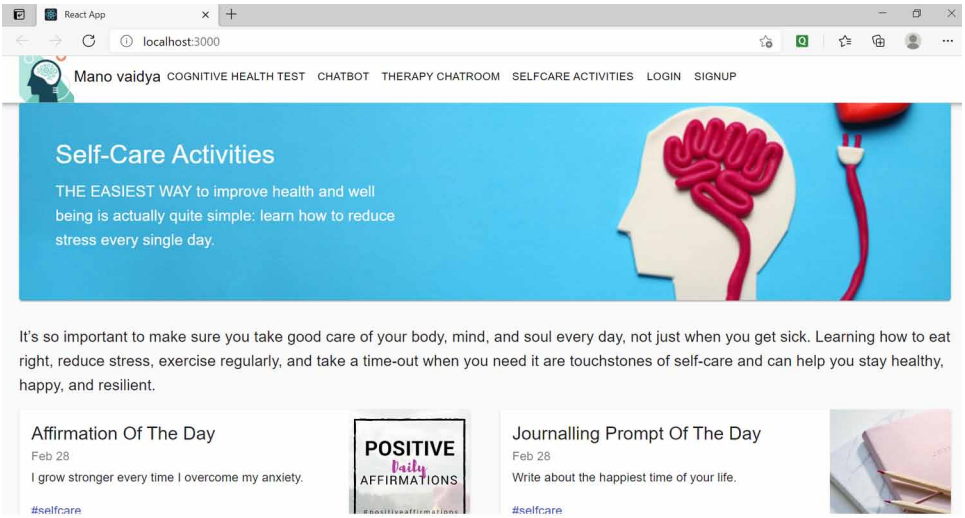


In figure 4, the self-care activity page is displayed that has activities that include yoga, inspirational stories, meditation, motivational routine.

In figure 5, the page depicts the Anonymous Therapy Chatroom which shows how a user can book session and attend the voice call for communicating with the anonymous therapist.

In figure 6, the page showcases the output between the user and Noddy the AI chatbot. The example used gives the user information about ManoVaidya.

Figure 4. Self-Care Activities



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Figure 5. Therapy Chatroom

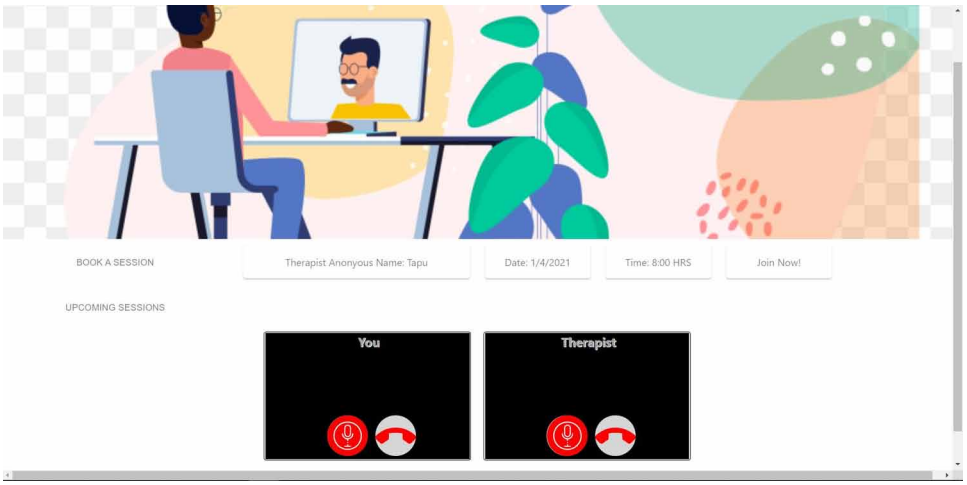
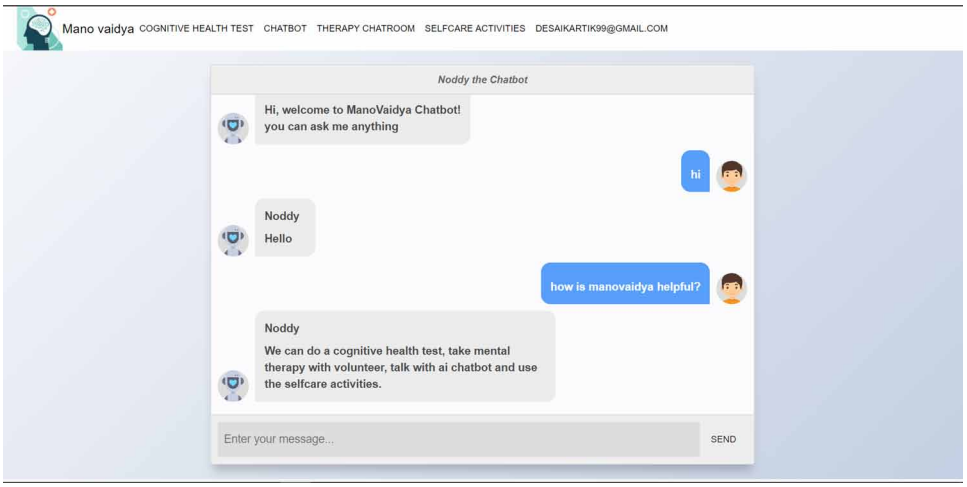


Figure 6. Chatbot



VALIDATION OF RESULTS

The trained model after development and training is validated on different test cases by a professional counsellor Sachi Shah and the accuracy achieved by the developed model is 80%. Figure 7, shows the validation of test cases by a professional counsellor.

In figure 7, the inference of a professional counsellor and the output of the proposed solution is validated by taking in consideration of few test cases.

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Figure 7. Validation of results

Questions	Response 1	Response 2	Response 3	Response 4	Response 5	Response 6	Response 7	Response 8	Repsonse 9	Response 10
1	15-25	15-25	15-25	26-35	26-35	36-45	45-55	55+	36-45	26-35
2	Male	Female	Male	Male	Female	Female	Male	Female	Male	Male
3	Student	Service	Student	Sevice	Businessman	Freelancer	Bussinesman	Retired	Freelancer	Student
4	Not at all	Some of the days	Several Days	Nearly Everyday	Nearly Everyday	Several Days	Nearly Everyday	Several Days	Some of the days	Some of the days
5	Not at all	Some of the days	Several Days	Nearly Everyday	Some of the days	Several Days	Not at all	Nearly Everyday	Several Days	Not at all
6	Not at all	Some of the days	Several Days	Nearly Everyday	Nearly Everyday	Some of the days	Nearly Everyday	Nearly Everyday	Some of the days	Some of the days
7	Not at all	Some of the days	Several Days	Nearly Everyday	Nearly Everyday	Some of the days	Nearly Everyday	Several Days	Some of the days	Not at all
8	Not at all	Some of the days	Several Days	Nearly Everyday	Nearly Everyday	Not at all	Not at all	Several Days	Some of the days	Some of the days
9	Not at all	Some of the days	Several Days	Nearly Everyday	Nearly Everyday	Some of the days	Not at all	Several Days	Not at all	Several days
10	Not at all	Some of the days	Several Days	Nearly Everyday	Nearly Everyday	Nearly Everyday	Not at all	Nearly Everyday	Some of the days	Not at all
11	Not at all	Some of the days	Several Days	Nearly Everyday	Nearly Everyday	Some of the days	Nearly Everyday	Several Days	Several Days	Some of the days
12	Not at all	Some of the days	Several Days	Nearly Everyday	Nearly Everyday	Several Days	Not at all	Several Days	Some of the days	Not at all
13	Not at all	Some of the days	Several Days	Nearly Everyday	Nearly Everyday	Some of the days	Not at all	Nearly Everyday	Some of the days	Nearly Everyday
14	Not at all	Some of the days	Several Days	Nearly Everyday	Nearly Everyday	Not at all	Nearly Everyday	Nearly Everyday	Not at all	Some of the days
15	Not at all	Not at all	Some of the days	Several Days	Some of the days	Several Days	Some of the days	Not at all	Some of the days	Nearly Everyday
16	No	No	No	No	No	Yes	No	No	Yes	No

Output by Manovaidya Application	**None**	**Mild**	**Moderate**	**Severe**	**Moderate**	**Mild**	**Mild**	**Severe**	**Mild**	**None**
Inference by Counsellor- Sachi Shah	**None**	**Mild**	**Moderate**	**Severe**	**Moderate**	**Moderate**	**Mild**	**Severe**	**Mild**	**Mild**

FUTURE RESEARCH DIRECTIONS

Social Media Crawler – a module where the system can be aware about the user's depression using the sentiments of the words used by the user on his/her various social media platforms. Social media sites have the potential to play an important part in the diagnosis and care of mental health disorders. Sentiment analysis along with natural language processing can be implemented to monitor depression of a user from the data collected from their social media handles.

Mood Emoticon - a feature that shows different mood based emojis where the user will select different emojis based on his or her current mood and using that prediction of the user's current mood will be predicted.

Therapeutic Digital Games – a feature where users can play different computer based cognitive behavioral therapeutic games for positive mental health. Games are an excellent way to deal with anxiety or depression. Various games can be added according to different mental disorders such as depression, anxiety, impulsion disorder, stress, attention deficit disorder and hyperactive disorder.

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COMPARISON WITH RELATED WORKS

Table 4. Comparison between this research work and previous related works.

Related Works	Current Research Work
Used algorithms like Apriori, Logistic Regression, Support vector machines and neural networks for mental health detection.	Uses Random Forest algorithm which has given a betterment in accuracy than previously used techniques.
Provides solutions for mental illness such as Yoga, Meditation and Therapeutic sessions.	Provides more solutions for mental illness like Self-care activities which contains motivational routines, yoga, meditation, inspirational stories, motivational articles to maintain positive cognitive health.
One to one therapeutic session for people in need of help by professional therapists through video calls.	Anonymous one to one therapeutic session for people in need of help by professional therapist through VoIP calls for privacy which is an opportunity for users to have a safe haven to converse freely with therapists.
Chatbots were developed by focussing on positive psychology & emotional intelligence through pre-programmed responses.	Chatbot here uses previous techniques and also adds precision therapy as pre-programmed input responses provided by a professional therapist for improved effectiveness.

CONCLUSION

In this work the authors have proposed a way of providing cognitive health assessment and offering different methods of helping people to cure problems arising from mental health disorders using artificial intelligence. The machine learning model the authors have trained has achieved accuracy of 71% in the cognitive health assessment module. The trained model after development and testing was validated by a professional counsellor where the model achieved accuracy of 80%. The proposed system will offer features like therapy chatroom where people in need of therapy from a professional will be provided a platform to communicate, users will have access to various self-care techniques provided to help and monitor their mental state with the help of activities like yoga, meditation, inspirational stories and motivational routine also an AI chatbot is on the system for any user queries. With this solution the authors aim to decrease the effect of mental illness at the early stages and help people lead to a mentally and physically fit lifestyle.

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KEY TERMS AND DEFINITIONS

Artificial Intelligence: Artificial intelligence (AI) refers to computerised artificial intelligence models designed for thought and emulation of human behaviour. The word may also apply to any computer that has characteristics similar to a human mind, such as problem solving and knowledge.

Cognitive Behavioral Therapy: Cognitive behavioural therapy (CBT) is a type of psychotherapeutic counselling that teaches people how to understand and change harmful or disturbing thought patterns that influence their attitudes and emotions.

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Cognitive Health: The ability to think correctly, read, and recall is referred to as cognitive health. Cognitive health is a vital aspect of carrying out daily tasks.

Machine Learning: Machine learning is a data processing tool that automates the construction of analytical models. It is an artificial intelligence division that assumes that systems should learn from their input, recognize trends, and determine with little human interference.

Mental Health: A level of well-being in which a person knows his own ability, is able to meet regular life pressures, work productively and successfully and contribute to his/her society.

Random Forest: Random forest is used to multiple decision trees that can be merged into one form. Predictions made by decision trees (or individuals, in particular) cannot be correct but, in combination, predictions are on average closer to the target.

Sentiment Analysis: Sentiment analysis is the systematic discovery, retrieval, quantification, and investigation of affective states and subjective information using natural language processing, text recognition, computational linguistics, and biometrics.

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Chapter 6
Artificial Intelligence and Machine Learning-Based Advanced Depression Detection System

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ABSTRACT

Depression can be called a health issue that majorly affects the stability of the mind. Depression can also be called a mood disorder or mental illness that affects our mental state. Depression can affect a person mentally and physically. According to WHO, 264 million people in the world are affected because of depression. At its worst, depression can lead to suicide. About 8 million people commit suicide every year because of depression. It is not possible for one to live with depression, but if they get proper treatment at a right time, depression can be controlled and cured to help the person to live a quality life. To identify the level of depression of a person, we have to first identify the type of depression the patient is going through. The type of depression plays a very important role in determining the kind of treatment or help a depressed person needs by providing them various treatments. The authors propose a solution for detection of depression type and depression levels using advanced machine learning and artificial intelligence algorithms.

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1. INTRODUCTION

Depression has become more prevalent in individuals of all ages and occupations, and it has developed into a severe psychiatric disorder that affects a person's mental and physical health; it is based on how we accept situations and how it works on the catalyst that is transmitted to the nervous system. When demotivation and depression persist for an extended amount of time, it has an effect on brain-based abilities such as memory and concentration. As a consequence, it's important to consider sadness and discern between depressed and sad individuals. The person's mood is first affected by depression, which lasts for a long time and remains the most prominent sign of depression. It has an effect on how the body functions, such as low energy, depressive thoughts and emotions, memory, and focus. It has the ability to disrupt brain activity and result in severe disabilities such as panic attacks, anxiety, and terror. Depression is not the same as sorrow. Researchers believe that depression is triggered by a variety of factors, including faulty mood control by the brain, genetic instability, traumatic life experiences, drugs, and psychiatric issues. It may be all of these factors combining with one another that cause depressive symptoms and effects on a person's physical health. Stress and mental distress, which are sometimes identified with the proletariat or working class, are rarely associated with university students, and are not well recognised as serious illnesses. According to the Association for Medical health in India, 33.92 percent of medical students reported moderate to high stress, 45.8% of postgraduate students reported stress, and 27.6% of orthopaedic trainees reported stress (Abdulla et al. 2013).

Aside from everyday meditation and mindfulness, the most effective way of preventing depression in teenagers is to encourage them to share their thoughts and desires with trusted adults. However, with rising anxiety, it is becoming tougher for people to locate someone who can ensure their documents' secrecy. In this article, we suggest an intelligent Android programme that can be used by people on the go to help detect whether or not they are stressed. In this step, the individual must answer a series of questions from which the percentage of depression will be determined using different machine learning algorithms. The user would also be given relevant tips for overcoming depression, with their progress being monitored for the next seven days. Depression is the most prevalent psychiatric condition and the main cause of injury. Depression is very common in women of all ages in India. Despite the fact that effective depression care occurs, In both cases, it does not hit the majority of sufferers wealthy and impoverished nations. In this respect, various research disciplines and scholarly studies have been undertaken. This paper provides background information on depression and machine learning, as well as a summary of previous research that used machine learning to diagnose depression, along with their benefits and disadvantages (.

Mental disorders may be defined by analysing how a person acts, feels, perceives, or thinks over the course of their lives. A significant number of people today are overwhelmed by the quick pace of life. Mental illness may be caused by stress and depression. Workplace pressures, working environments, people we associate with, daily schedules, eating habits, and so on are some of the major factors that contribute to the development of stress. Stress can also manifest itself in normal activity when carrying out day-to-day tasks. Individuals may use social media to communicate with peers and share their everyday routines. As a consequence, data from social media platforms can be used to track tension. There are various methods for detecting stress levels (Othieno et al., 2014). Some devices are used to measure stress, while a diagnostic examination is used to determine the degree of stress. There are also applications that evaluate a person's actions to detect stress. Many researchers have attempted to use ML algos, such as the Decision Tree, Naive Bayes, Random Forest, and other algorithms, with results

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averaging 70% accuracy. Suicide is 17th biggest reason for death in world, which causes 1.4 percent of all fatalities. The bulk of these deaths occur in countries with low and middle incomes. Since 90% of those who commit suicide have a significant mental condition, illnesses, the most common of which is depression, treating mental health issues is the only way to mitigate or avoid suicide. Many people commit suicide as a result of a lack of adequate care. A loved one's passing, a divorce, or the end of a relationship, being abused, and physical violence are all factors that can lead to depression. People who are depressed often feel totally alone. Mental wellbeing advocates, on the other hand, encourage people to engage and seek support. The best thing a depressed person can do is reach out and talk about their emotions before acting on them. There are helplines/crisis lines for those who are suffering, but often people who are considering suicide do not use such resources because they are afraid or embarrassed to speak up for themselves. In these types of cases, people must be able to communicate their thoughts and feelings without having to think about the aforementioned problems.

Social networking may be abused due to the large amount of information, which applies to consumer behavioural traits. Using the data to predict a social media user's mental health status will assist a doctor, family member, or acquaintance in providing timely medical advice and counselling to a depressed user. Depression is one of the world's most dangerous illnesses, according to WHO? Furthermore, almost two-thirds of people who are suicidal do not pursue proper treatment, which may have significant effects. Medical science relies on telling people about their lives, which makes it difficult to make a definitive diagnosis of depression. During a three-week cycle, the patient must attend more than one session. A False Positive problem occurs when a non-depressed condition is labelled as depressed. However, scientists and doctors found discovered that the (EHR) programmes were unsuitable for integrating mental health and primary care.

Depression counts as a significant health issue due to its wide presence and, as a result, the misery, dysfunction, morbidity, and economic burden it creates. It's a severe enfeebling condition that affects people of all ages and can trigger symptoms such as low mood, remorse, insomnia, and complications such as back pain and bilateral medication symptom, as well as being fatal if not treated. According to the World Health Organization (WHO), nearly 450 million square units of humans suffer from depression today. Depression is one of the most dangerous illnesses in the world, according to the United Nations.

Depression is a common psychiatric condition that has the potential to lead to suicide. It is also a major source of disabilities around the world. Greater than 400 million people worldwide are believed to have depression per year. Face-to-face psychological depression guidelines are commonly used to detect depression. However, 70% of people in the early stages of depression would not seek medical assistance, which may lead to their illness deteriorating. There has recently been a push to use social media data to identify, estimate, and monitor improvements in the prevalence of diseases. Because of its extensive use, social media provides a variety of resources for mental health providers and analysts to expand the evidence they have access to, resulting in a better-informed and educated mental health industry. Mental disorder is a recognised factor that leads to suicide; about 70% of those who try suicide possess a mental disease diagnosis. Depression is the most prevalent mental disorder, but it has gone undiagnosed or untreated due to a lack of understanding or denial. Early detection of major depression symptoms and treatment with prompt intervention will help to avoid the occurrence of depression (Peng et al., 2019).

People's wellbeing is increasingly becoming jeopardised by psychological stress. People are getting more anxious as the speed of life quickens. According to a global report released in 2010 by New Business, more than half of the world has seen an increase in tension in the last two years. Despite the fact that stress is non-clinical and normal in our lives, it can be dangerous if it is excessive or chronic to human

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health. According to a new review, long-term stress has been related to a variety of diseases, including clinical depression, insomnia, among other illnesses. According to the Centres created for controlling the disease and preventing it, suicide has since been a leading reason for the death among teens, and unnecessary stress counts as a huge factor in suicide. As a result, the exponential growth in tension has become a major threat to health as well as quality of life. As a consequence, identifying tension before it becomes a serious concern is important. Face-to-face interviews, self-assessment questionnaires, and wearable sensors are the most common methods for detecting psychological tension. Traditional approaches, on the other hand, are reactive and are typically labour-intensive, time-consuming, and hysterical. Are there any strategies for detecting stress that are both timely and proactive?

The main aim of this paper, "Artificial Intelligence and Machine Learning Based Advanced Depression Detection System," is to overcome that limitation by allowing users to openly communicate their feelings and emotions in a private and confidential environment using various Artificial Intelligence and Machine Learning Algorithms to an artificial companion who listens and tracks their actions. Medical decision-making, treatment, diagnosis, self-help, and behavioural health care management are also areas where artificial intelligence (AI) technologies and approaches are being used. The expert system provides expert advice and therapy to help individuals overcome suicidal thoughts. This project is about creating a virtual human conversation with the system to help users communicate in a mental health environment. It offers confidential online healthcare advice and assistance, and the app may act as a clinician or psychotherapist. It makes use of Android technology, which is especially useful for mental health applications. This project creates a framework that uses Artificial Intelligence and Machine Learning algorithms to calculate depression levels. As a consequence, this application has the potential to make a huge difference in people's lives by improving their mental health. This approach is often associated with Artificial Intelligence, specifically machine learning algorithms.

TYPES OF DEPRESSION

Major depression: Significant depression, the most common form of depression, is characterised by the all-gloomy mood and a loss of pleasure in hobbies, including those that are normally pleasurable. Trouble sleeping, increases in appetite or weight, fatigue, and a sense of worthlessness are all symptoms of this form of depression

Persistent depressive disorder: This category of disorder, formerly known as "dysthymia," refers to a depressive and lasted nearly two years but does not exceed the intensity of severe depression.

Bipolar disorder: Bipolar disorder, formerly known as manic-depressive syndrome, is characterised by depressive episodes. They do, however, experience periods of extraordinarily high energy or movement.

Seasonal Affective Disorder (SAD)

This type of depression emerges as days get shorter in the fall and winter. The mood change may result from alterations in the body's natural daily rhythms, in the eyes' sensitivity to light, or in how chemical messengers like serotonin and melatonin function.

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Perinatal Depression

Significant and minor depressive episodes that occur during pregnancy or within the first 12 months after delivery are classified as this form of depression (also known as postpartum depression).

PMDD

Premenstrual syndrome, or PMS, is the cause of this type of depression. PMDD symptoms normally appear shortly after ovulation and disappear once menstruation begins. SSRIs like fluoxetine (Prozac) and sertraline (Zoloft) can help to alleviate symptoms.

2. RELATED WORK

Suicide is a big problem all over the world. Untreated depression is the leading cause of suicide. As a result, it was agreed to pay closer attention to and recognise depressive signs in order to avoid suicide attempts. Talking about their emotions with someone they trust and releasing their pain inside is the best way to treat depression. Suicide is the world's 17th leading cause of death, accounting for about 1.4 percent of all deaths.The majority of these deaths occur in countries with low and middle incomes. Since 90% of those who commit suicide suffer from severe mental illnesses, the most common of which is depression, treating mental health issues is the only way to mitigate or avoid suicide. Many people commit suicide as a result of a lack of adequate care. A loved one's passing, a divorce, or the end of a relationship, being abused, and physical violence are all factors that can lead to depression. People who are depressed often feel totally alone. Mental wellbeing advocates, on the other hand, encourage people to engage and seek support. The best thing a depressed person can do is reach out and talk about their emotions before acting on them. There are helplines/crisis lines for those who are struggling, but often people who are considering suicide do not use such resources because they are ashamed or embarrassed to speak up for themselves. In these types of cases, people must be able to communicate their thoughts and feelings without having to think about the problems. Depressed mood swings, lack of interest in everyday activities, feelings of emptiness, hopelessness, and other secondary MHDs are all common symptoms. The rate of occurrence is highest in adulthood, when family and job commitments are most likely to be affected. These forms of depressive disorders rarely last, and the number of people who recover from them is relatively high. However, although the majority of people who are depressed recover, a significant number of those who are depressed remain chronically depressed, and those who do improve have a greater risk of having more episodes as they progress in life. Suicidal thoughts, engaging in self-harming behaviours for themselves or others, and even committing suicide/murder on themselves or others are just a few of the major consequences of such regular encounters (Abdul-Mageed et al., 2011).

Depression is a common cause of mental illness that has been linked to an increased risk of dying young. Furthermore, it is a major contributor to suicidal ideation and has a huge influence on everyday life. Depression is a mental condition that can affect multiple aspects of one's life. It has far-reaching and varying effects, considering its invisibility. The pressures of everyday life events can increase the risk of depression in today's world. If at least five of the following symptoms occur almost every day for at least two weeks, it is diagnosed:

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1. Suffering from a Depressed Mood
2. Suicidal thoughts
3. Loss of interest in activities
4. A sense of inadequacy or hopelessness
5. Worsened facility to celebrate and concentrate

There might be other reasons like genes and family history which might additionally lead to despondence.

Depression is a psychiatric disorder influenced by a variety of causes, including daily stress, physical activities, and physical diseases. It is associated with conditions such as persistent melancholy, slumber disease, and attempts at suicide. It is necessary in healthcare to correctly predict various conditions. As a result, in order to maintain noetic fitness, it is essential to assess individuals' circumstances and continue to treat them. In the field of noetic diseases and care, research has been done to determine a patient's status using massive amounts of data and to track the worst case scenario. Dejection is a frequent symptom of phrenic illnesses.

People now suffer from severe physical ailments and psychological trauma as a result of a combination of internal and external causes. People's feelings change based on where they are, such as at school, work, or a conference, as well as the weather and time. Those who often experience despondency, lack of exuberance, or dysthymia are more vulnerable to despondency. Despite the fact that dejection is most commonly associated with adults in their 30s and 40s, it is also observed in juveniles due to academic tension, as well as in the elderly. As a result, despondency is a phrenic disease that people of all ages are affected. Patients having phrenic illnesses tend to obnubilate their disease due to a socially pessimistic attitude toward them. Symptoms like depression, a sense of ebullience, and dysthymia are normal enough in therapy that they are easily missed. According to Health Indemnification Analysis and Appraisal Accommodation's data on diseases of national importance in healthcare, the number of suicidal patients and treatment expenses continue to grow (Ibrahim et al., 2013). Patients in their 50s and 60s who seek medical help with their depression are the majority. It denotes that adolescent adults struggle to make sufficient aversion, care, and recovery choices in their responsible lives. More requests for timely treatment and continuing care by early diagnosis are on the rise in this case. Melancholy has a high cure rate if caught early, but it is likely to recur. Phrenic illness is a common human ailment. According to studies, 44 million Americans, or 19% of the adult population, are affected by noetic disease each year. In the past year, 16 million people (7 percent of Americans) have had at least one major depressive disorder. Kids born to depressive parents have a greater risk of psychopathologies like melancholy, ADHD, and substance addiction, according to previous study.

The main goal of early melancholy identification is to recognise people who are showing signs of depression so that appropriate care and medication can be provided as soon as possible. When left untreated, depression may have side effects that are not related to the condition, such as an increased risk of dangerous behaviour such as opioid or alcohol use, making it difficult to recover from more serious diseases, and the disease itself can be perpetuated for years by psychiatric despondency. According to the WHO, India had the largest number of suicide cases in 2012, with one person committing suicide every 40 seconds. Dejection is a major cause of ecumenical incapacitation, and it also contributes greatly to global epidemic anxiety. Women are more likely than men to be depressed, which almost often leads to suicide. India's population is currently projected to be about one billion people. According to a World Health Organization study conducted in 2015, one out of every five Indians suffers from depression.

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According to a WHO survey conducted by NCMH (National Care Of Medical Health), the likelihood of patients suffering from melancholy in India is about 6.5 percent. Despite the abundance of appropriate therapies, there is a significant scarcity of counsellors, therapists, and medicos, many of which are known as phrenic wellness staff. According to WHO, the percentage of those jobs is "1 in 100,000 individuals"? In India, the average rate of suicide due to depression is around 10.9 per 100,000 people, and the average age of those who commit suicide is under 44 years.

Much recent research has shown a relationship between mood changes and transmuted emotional attention. The analysis of audio features can be a consequential implement to avail in despondence identification and monitoring throughout depressive disorder and recuperation. In such a low mood, the voice of human beings appears different from the ones in mundane states.

There is a growing body of study on the symptoms of despondency. Choudhury et al. argue that despondency is a true measure of one's own and society's well-being. A large number of people suffer from the negative symptoms of depression, but only a small percentage receives adequate care each year. They have looked at the possibilities for using the internet to find and measure the symptoms of depression in individuals. They quantified behavioural credits associated with convivial interaction, feeling, and modes, a sense of self-esteem, and anti-depressant drug descries through their net-based gregarious networking. Choudhury et al. looked at internet networking as a potentially valuable method for human health, based on use of the Twitter application to create statistical models for the effects of childbirth on the actions and temperament of expectant mothers. They measured postpartum vicissitudes in 376 mothers using Twitter messages, as well as convivial participation, feeling, casual culture, and phonetic style. According to Thompson, Twitter is increasingly being investigated as a tool for assessing psychologically well-being, having despondency as well as sociality, in the general population. Using both human coders and a programmed computer classifier, they discovered that it is possible to identify the level of concern within suicidal tendency tweets. Zhang et al. also shown that people at high risk of suicide can be detected using online networking resources such as a micro blog. To save their lives, it is possible to implement a complex intervention scheme. Using mood, psycholinguistic methods, and drug topics abstracted from the posts engendered by persons from these groups, Vgeun et al used ML and predictive techniques to disentangle internet messages between depressed and the other control groups. Park et al. looked at people's attitudes and behaviours about internet-based gregarious networking, regardless of whether they were surprised or not. They scheduled semi-structured one-on-one meeting with 13 participating Twitter users, half of them were not having courage and the other 50% were unafraid. Aside from that, they looked at a few proposals that implied insinuations for potential convivial networks that could best suit users with depression and have bits of cognizance toward assisting bewildered users in resolving their problems by online web-based gregarious networking. Bachrach and his colleagues Bachrach and his colleagues looked at how users' Facebook behaviour contributes to their identity, as assessed by 5 Factor Model. They looked at the links between users' personalities and Facebook profile resources. For example, the scale and thickness of their amity network, the number of images transferred, the number of activities attended, the number of accumulating enrolments, and the number of times the individual has been tagged in photographs. Ortigosa et al. have demonstrated an incipient technique for opinion analysis in Facebook that proposes extracting details regarding the user's appraisal extremity (positive, neutral, or negative), as conveyed in the messages they inscribe; and displaying the user's normal inference extremity and distinguishing enormously monumental ardent improvements, starting from messages written by users. Holleran discovered preliminary evidence that despondency is a significant contribution to the overall ecumenical of diseases by Facebook mining. Rang at al. and Vhen

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Nt al looked at a number of despondence-related characteristics and created a multimodal depressive paradigm to classify suicidal people. Ingesting and weight gain, poor appetite and weight loss, recollection; ingesting and weight gain; loss of confidence in leisure activities and interests, including lack of focus and inability to make decisions, emotions of culpability, frivolousness, helplessness, restlessness, and exasperation; and suicidal noetic conceptions are the key psychiatric signs of despondence. If these effects are shown to create a huge impact on important aspects of a person's life, like education, work, or social events, this is a crucial clue for writing a psychiatric diagnosis. The 17 characteristics included age, academic qualifications, monthly income, work status, BMI, service duration, family form, marital status, prevalence (if any) of hypertension, diabetes, or ischemic heart disease, job history, location within the business, and types of vessels posted to, as well as dummy variables for academic qualifications and marital status used to collect data on the participants' jobs, sociodemographics, and dummy variables for academic qualifications and marital status used to collect data on the participants' employment, sociodemographics, and health. Catboost has the best accuracy of all classifiers, with 82 and 83 percent, respectively.

The most common psychiatric illness is depression, but it has remained undiagnosed or untreated due to a lack of awareness or denial. Early identification of major depression symptoms and treatment with prompt intervention will help to avoid the occurrence of a major depression. The main purpose of this study is to see whether the person is stressed based on the the content of his or her tweets, as well as his or her presence in the social media network It may also be used to describe other mental disorders, and it could also serve as the foundation for new mechanisms to diagnose and limit depression dissemination in social networks. Tsugawa et al. discovered that word frequency and subject modelling are important features for the prediction model. They got 69 percent classification accuracy SVM classifier with radial kernel in predicting depression in 81 of the 209 participants who filled out a questionnaire. Reece et al. also extracted predictive features from users' tweets for calculating impact, linguistic style, and meaning, supervised learning algorithms were used to build models that used these features and successfully discriminated between them. The CESD scores were calculated after depressed users were identified, and data was collected from 105 of the 204 depressed users. A 1300-tree random forest classifier was used to improve classifier efficiency, which improved the precision to .87 as compared to other study results. Nadeem et al. used the bag-of-words approach for better depression diagnosis, which uses word incidence rates to quantify the accuracy of a tweet measured on a text basis. They put four binary classifiers to the test: the linear SVM classifier, the decision tree (DT), the Naive Bayes (NB) algorithm, and the logistic regression method, and discovered that the NB algorithm outperformed the others with an accuracy of 80%.

People's wellbeing is being jeopardised by psychological stress. It is difficult to identify stress in a timely manner in order to provide preventive treatment. People have become accustomed to sharing the daily lives plus communicating along the peers on social networking sites, allowing data from these sites to be used to diagnose stress. We find that a user's stress level is directly, We use a large-scale sample from real-world social networks to systematically explore the connection between user stress levels and social interactions in this article, and we use a large-scale sample from real-world social networks to do so. Emotion identification at the tweet stage in social networks is the topic of research. In recent years, computer-assisted emotion detection, analysis, and implementation, especially in social networks, has gotten a lot of attention. Relationships in psychological tension and the personality characteristics are an intriguing issue to explore. Providing evidence, for example, that everyday stress can be accurately detected using behavioural indicators from users' mobile activity. Most analyses in social media-based

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emotion research rely on tweets, which are categorised using text-based linguistic features and standard approaches. Emotion recognition at the user level in social networks is the focus of research. In a recent paper, we proposed using to learn user-level presentation and Researchers used a deep convolutional network on a sequential tweet sequence over a specified time period to detect users' psychological stress states from social media. Utilizing social experiences for social network analysis is the subject of research. One of the most significant aspects of social media sites is social engagement. Many studies are now focused on how to use data from social interactions to increase the efficacy of social media analysis (Lin et al., 2017).

Depression has long been a cause of concern in our society and a hot topic among researchers all over the world. We gathered data from students and parents in real time by making them complete questionnaires that were similar to the PHQ-8 (Parent Health Questionnaire), which included questions like "What is your age?" Or do you go to school or college every day? Then, using attributes like age, sex, school attendance, and so on, converted it into usable data. Then, depending on severity, classification system algorithms are used a result, the misery, dysfunction, morbidity, as well as the financial strain it imposes. It's a severe enfeebling condition that affects people of all ages and can cause low mood, remorse, insomnia to train and categorise depression into five stages: minimal or zero, mild, moderate, fairly intense, and severe. The XGBoost classifier has the best precision of 83.87 percent in this dataset. Depression is a huge public health concern because of its severity and associated risks, such as debilitating back pain and bilateral drug side effects, among other factors. It can be lethal if not treated. According to the WHO, nearly 350 million square units of people are actually depressed. According to the United Nations, depression is one of the world's most dangerous illnesses (Grover et al., 2010).

Many commonly accepted forms and standards have been established based on the worldwide questionnaire survey. The CES-D Scale, for example, includes 20 questions about mental disorders such as one of Lenore Sawyer Radloff's associated works, users' negative feelings and sleeping situations are portrayed. The questions either provide several options of varying ratings or ask users to rate the severity of their case. Tzirakis et al. suggested a deep learning-based approach to analysing emotion as well as a person's depressive state, inspired by the application of deep learning in emotion identification. Internet-Relation Addiction, Overloading of information, and Net Compulsion are only a few of the social network mental disorders (SNMDs) that have recently been reported. Today, the signs of these psychiatric disorders are often detected passively, resulting in delayed therapeutic care. In this post, we argue that mining online social interaction will help you detect SNMDs early on.

A. Survey Responses-Based Forecast

The validity and reliability of psychometric self-report trials for psychiatric disorders are very high. In psychological and epidemiological research, self-report assessments are second only to clinical interviews, and no social media analysis has used clinical interviews as an outcome test to date. We looked at five studies that used social media data to merge participants' responses to depression surveys in order to measure depression status based on survey results. Before a recent episode of depression, the study with the most citations looked at Twitter behaviour to determine network and language data. The frequency and date of a recent depressive episode were registered, as well as the Centre for Epidemiologic Studies Depression Scale Updated and Beck's Depression Inventory ratings. Due to diurnal patterns, more suicidal sentiment, less social interactions, more self-focus, and citing depression-related words in the year prior to, depressed users' posting behaviour was shown to be different. Reece et al. used text and

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Twitter meta-data to forecast customer anxiety and posttraumatic stress disorder (PTSD) status before a reported first (PTSD). Data was aggregated to weeks, which performed slightly better than days, and modelled as linear trajectories of action patterns to distinguish stable and mentally ill users. Tsugawa et al. used the CES-D as their measurement parameter to predict depression from Twitter results in a Japanese study. Forecasts based on findings from a longer time span were less reliable; tweets from the most recent 6–16 weeks prior to the administration of the CES-D were satisfactory for predicting depression. Unlike other research, this one used Facebook status updates to make its predictions. Mothers filled out a questionnaire and self-reported a clear episode of postpartum depression (PPD). A model based on demographics, Facebook behaviour, and post content accounted for 36.5 percent of variation in the status before childbirth. Wartz rt al. users' constant anxiety scores through a wider community of Facebook users using questions from a personality questionnaire (N = 27 849) than previous research (N = 28 749) have used. According to this study, which looked at seasonal differences in depression, people were more depressed during the winters. This report has gathered a list of the most commonly associated depression terms, sentences, and topics (categories of semantically related words).

B. Mental Health Forecast Based on Self-Reported Results

Data that's freely available is employed in a very number of tests. Self-declared psychological state diagnosis on Twitter (identified by tweets like "I was diagnosed with depression today") is one such collection of publicly accessible evidence. we glance at seven of those reports. A workshop on linguistics and psychotherapy (CL Psych) has begun. Participants within the 2015 CL Psych workshop were asked to predict whether a Twitter user has PTSD or depression supported self-declared symptoms (PTSD n = 248, depression n = 328, with age and gender-matched controls) in 2014 to permit clinical psychologists and computer scientists to cooperate, which might assist within the creation of these research. 'Shared tasks' were produced using the identical data set to research and compare different solutions to the identical prediction challenge. Participants built language subject models (for example, an anxiety topic contained the words feel, worry, pain, study, time, and hard), sought for words most related to PTSD and depression, considered character sequences as characteristics, and used a rule-based approach to make relative counts of N-grams present altogether users' PTSD and depression statuses. In terms of estimation, the latter got the higher score. Both approaches showed that distinguishing between PTSD and depression was tougher than identifying the involvement of either condition as applied to controls, suggesting that the language correlated with both conditions is analogous.

C. Forum Participation-Based Estimation

A source of publicly available mental state text is online forums and pages created for discussion. They provide a secure atmosphere for people to hunt care, receive and supply social help, and publicly explore stigmatised psychological state problems. during this paper, three such studies are discussed. The health of scholars studying in US universities was analysed using posts from the net (reddit). A predictive model is trained on the information collected from its mental state help groups and were accustomed the posts received from 110 universities subedits to quantify extent of hysteria within the university. During the tutorial year, the amount of mental state positions increased, especially at universities that managed on a quarter-by-quarter calendar instead of a semester-by-semester calendar. Vocabulary of 17 subedits describing number of psychological state issues was represented using LIWC and other sentence complex-

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ity markers. DE Jason examined the posts within the group members who first discussed psychological state issues before moving on to debate suicidal ideation later. This transition was followed by increased self-focus, poor linguistic style matching with the group, decreased social interaction, and expressions of hopelessness, anxiety, impulsivity, and alienation.

D. Forecast Based on Annotated Articles

Manually editing and annotating Tweets containing psychological state keywords resulted within the development of the publicly available text. Annotators use top-down (theory-driven) or bottom-up (data-driven) classifications to categorise social media messages; annotations will be predicted using post language. within the field of behavioural sciences, big data involves the prevention of cross-validation. the bulk of depression annotation research focuses on finding posts where users discuss their own depression experiences. Annotators are trained to recognise a good range of stress signals seen in medical assessment manuals just like the DSM-5, furthermore as a more limited collection of symptoms sort of a depressed mood, disrupted sleep, and exhaustion. Since then, annotation has been accustomed distinguish between references to mental disease intended to stigmatise or ridicule it and people intended to specific empathy or provide valuable information to those that are stricken by mental disease generally, post annotations are a helpful (but time-consuming) method for identifying life circumstances associated with psychopathy that are not protected by standard depression diagnosis guidelines. The proposed system is compared with various existing systems is as follows

Box 1.

Existing system	Our proposed system
1. In the current existing system depression is calculated by analysing various social media platforms, using chat bots, etc.	1. In our proposed system real time prediction is done by asking various questionnaires related to predict depression.
2. Current system consists of depression detection models only.	2. Our proposed system consists of depression detection model along with various treatments or solutions to cure depression.
3. Current system predicts depression without considering professions of the patient.	3. Our proposed systems consider profession of the patients like Student, Teacher, etc. This indeed helps to improve accuracy of depression prediction.
4. Current system only predicts depression and do not take day to day follow up to trace patient's recovery.	4. Our proposed system takes day to day follow up to monitor the recovery of patient.

3. PROPOSED SYSTEM

3.1 Proposed Approach

Melancholy is a phrenic disorder that can impair many of the facets of a person's life. Though it is not facilely detected it has profound and sundry impacts on humans. In today's world, the stress of daily life events can increment the chances of melancholy. According to Health Indemnification Analysis and Appraisal Accommodation's data on diseases of national importance in healthcare, the number of suicidal patients and treatment expenses continue to grow. The bulk of people receiving care for depres-

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sion are in their 50s and 60sIt denotes the puerile adults are unable to make sufficient aversion, care, and recovery choices in their everyday lives. More requests for timely treatment and continuing care by early diagnosis are on the rise in this case. Dejection has a high degree of regeneration if caught early. Despondence has many symptoms, out of the below-mentioned symptoms 3 – 4 occur to a dispirited person on customary substratum -

1. Poor mood
2. Lack of confidence in normal life
3. Suicidal celebrations
4. Feeling of hopelessness
5. Worsened competency to celebrate and to concentrate

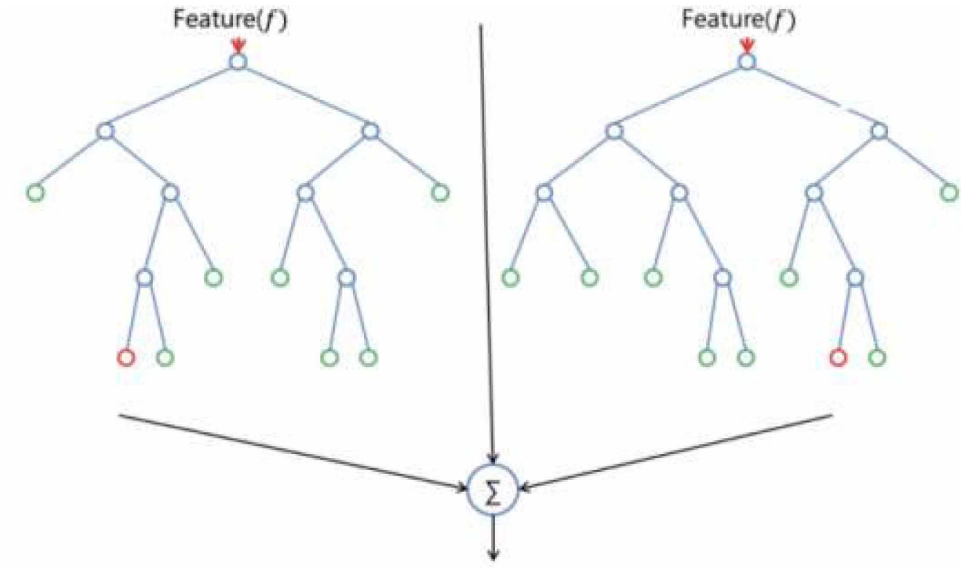
In our proposed system we incline to sense the following symptoms in the patient by asking sundry questionnaires. Predicated on the replication of utilizer despondence level will be calculated by applying Desultory forest algorithm and result will be exhibited instantly.

3.2 Used algorithm (Random Forest)

Random forest is a supervised Machine learning algorithm which creates a forest. The "forest" that the algorithm produces is a set of decision trees that have been trained using the "bagging" technique. The bagging approach is based on the premise that integrating multiple learning models boosts the final outcome.

One of the most massive benefits of the arbitrary forest is that it can be used to solve both relegations and regression problems, which account for the majority of modern ML systems. You can see how a desultory forest will resemble two trees in the image below:

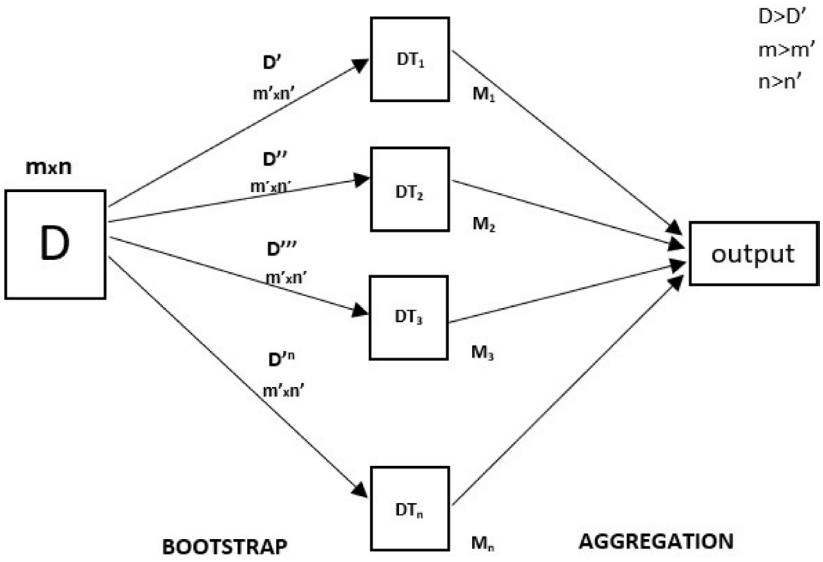
Figure 1. Random Forest Model



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Since each decision tree is impeccably trained on the same sample data, the resulting variation is low as all of them are combined in parallel. As a result, the performance appears to be dependent on multiple decision trees rather than one. In the event of a relegation dilemma, the plurality vote classifier is used to determine the final result. The final value in a regression quandary is the average of all outputs. Aggregation is the name of this variable.

Figure 2. Aggregation model

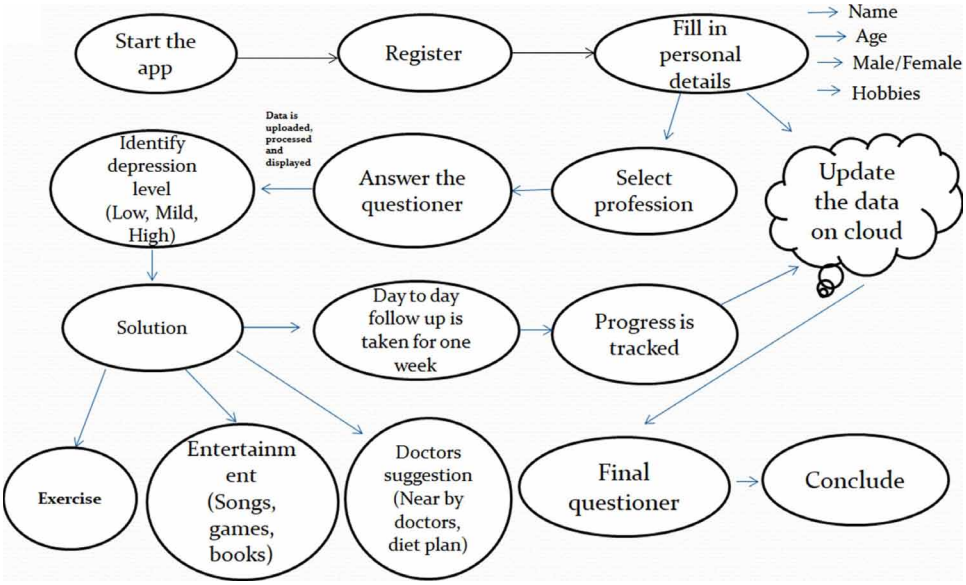


An arbitrary forest's hyper parameters are the same as those of a decision tree or a bagging classifier. Fortunately, a decision tree and a bagging classifier aren't needed since a desultory forest's classifier-class can be used instead. The consumer can use the algorithm's repressor to complement regression tasks with desultory forest. When increasing the leaves, an arbitrary forest may be used to incorporate adscititious desultoriness into the model. Rather than looking for the supreme feature when breaking upon the node, the algorithm looks for the supreme feature within the small number of options. As a consequence, there is a lot of variance, which leads to a better model.

As a consequence, the algorithm for separating a node in the desultory forest only considers an arbitrary subset of the functionality. Instead of probing for the best possible thresholds, you can make trees even more desultory by using desultory thresholds for each purpose. Another great benefit of the arbitrary forest algorithm is how simple it is to quantify the relative significance of each function in the prognostication. Sklearn possess a good tool for above purpose that tests a feature's paramountcy by examining how much the tree nodes that use the function reduce impurity in the forest as a whole. It calculates aboce score for every function automatically after the training and scales the results such as that the sum of all becomes equal to 1. By visually inspecting the functionality paramountcy, the consumer may assess which features should be omitted because they don't add sufficiently to prognostication process. It is very important because, according to a rule of machine learning, The greater features your sample has, the more likely it is to be overfitted, and vice versa.

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Figure 3. Depression Detection System Architecture



As a result, the algorithm for splitting a node in random forest only considers a random subset of the functionality. You can make trees even more unpredictable by using random thresholds for each variable instead of searching for the best possible thresholds.

Other good advantage of random forest algorithm is how easy it is to determine the relative significance of each attribute on the prediction. Sklearn possess a good tool for this that assesses the value of a function by evaluating how often the tree nodes that use it minimise impurity across the entire forest. After practising, it calculates this score for each function and scales the results so that the total importance equals one. By examining the value of features, the user may assess which features should be dropped as they do not have any significance contribution to the prediction. It is very important because, according to a rule of machine learning, The greater features your sample has, the more likely it is to be overfitted, and vice versa.

3.3 System Model

Android is used to construct the framework in the implemented model. Android offers a rich application platform that allows users to develop creative mobile apps using the Java programming language. The patient's information is stored in Firebase. Google's Firebase is a mobile app development platform that enables users to create, upgrade, and scale their apps. Machine learning algorithm is implemented in eclipse.

1. The user (if new) creates an account on the application by filling in some personal details like name, age, hobbies, profession etc. All the details will be saved in the Google firebase system for further use.
2. Depending upon the profession of user the application will provide a questionnaire to determine the mindset / mental condition of the user.

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3. User completes the questionnaire by selecting appropriate options.
4. Answers given by the user will be saved and processed using the Machine learning algorithm to predict the depression level of user.
5. Depending upon the depression level calculated the user will be provided with basic treatment like:
   a. Healthy Diet chart for the user will be generated.
   b. Necessary Exercises which will help the user to relax will be provided.
   c. Fun games for relaxation will be available on the application.
   d. Motivational music will be provided.
   e. If necessary contact of psychiatrist near the location of the user will be provided.
6. Regular follow ups of the user through questionnaire will be taken to track the treatment process of user.

4. RESULT AND DISCUSSION

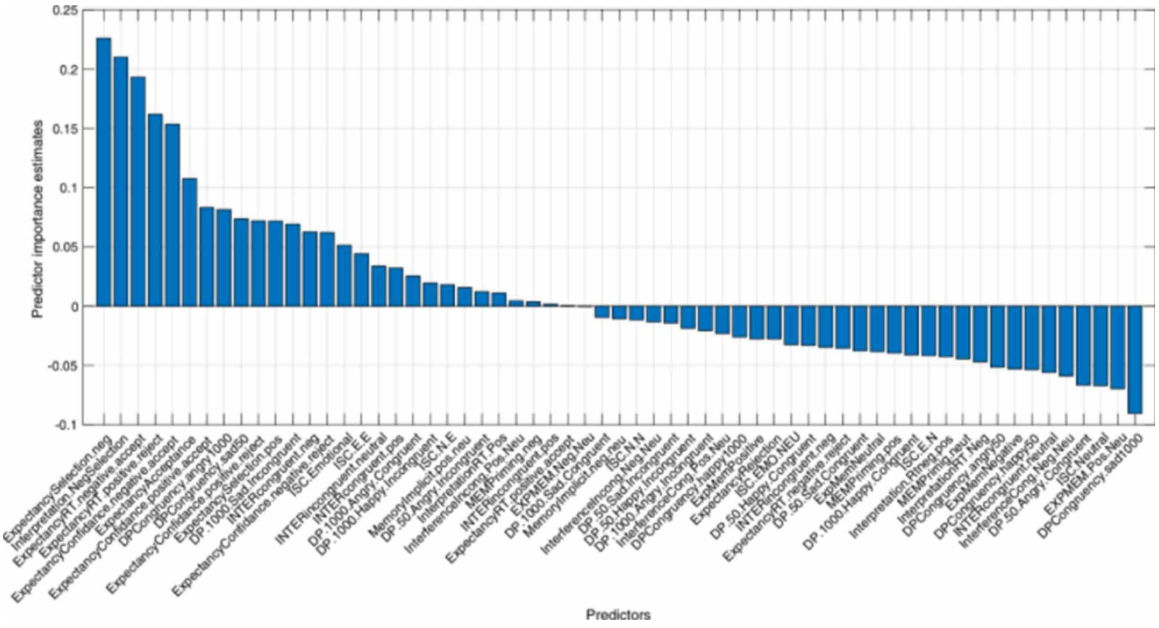
Procedure for internal role switching the emotional version is an example. At the centre of the screen, emotional and neutral words are shown in order. On their own, participants are asked to list how many negative and neutral words they have. After a few experiments, they are asked to report the number of words in each mental count set.

The trees were engineered to be appropriately adaptive and capable of classifying participants into the four study classes using a machine-learning research methodology based on a random forest algorithm. A random forest is made up of 1,000 decision trees (in this study), each of which is made up of a feature selection mechanism, which is built into decision trees, aids in avoiding data over-fitting series of rules that separate the input data into more homogeneous groups in terms of questionnaire labelling. The process is repeated if there are participants in sub-groups with various questionnaire classifications. When the groups and the sub-groups are homogeneous, process is complete. At each iteration, the group is split into two sub-groups by applying thresholding to one of the input stages. In this way, steps that do not have a clear separation of data into homogeneous subgroups will be withdrawn from the system. Every tree has a specified set of rules, but all of them start from the same training data. The use of a random forest facilitates accurate classification in the face of considerable variance in measurements within each division since the forest allows for a large number of repetitions (trees) in the classification process. In this way, slight trends can be seen in the classification data.

Each behavioural prediction makes a minor contribution. The normalised error discrepancy in grouping all behavioural traits with and without each individual measure is plotted on the X axis. The greater the difference, the greater the contribution of the behavioural measure. The greater the disparity, the more important the behavioural measure's specific contribution. The value of the jth function is calculated as follows: Validation is done twice for the trees gathered during the training phase: once for the original dataset and again for the same dataset with the jth feature's data permuted in all the participants, In each tree, the error difference between the two runs is estimated, resulting in a sequence of differences of one difference in each tree. As a consequence, the average of the error series divided by its standard deviation is the jth function importance. Steps to the left of the zero-point were used in the bagged tree algorithm, which improved the model. Only interventions that had a positive impact were used in the 'leave-one-out' study. Twenty-seven of the 61 behavioural approaches studied were found to help the model predict better. As seen on the left of the X axis, the proportion of acceptance of negative sentences in the FET,

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Figure 4. Predictor Estimates



which measures expectancy biases, was the most applied. The percentage of negative selection in the WSAP, which assesses interpretation biases, was then ranked in order of decreasing negative selection. An index of sad facial expressions which was shown over 1,000 milliseconds was the most unimportant feature of it. As a result, the final algorithm did not include this metric.

The processing of training data is critical to the training process. The whole forest classification process is repeated a thousand times to remove any selection bias. Every run involves a random collection of the training package, as well as a random selection of each participant about 25 times. The system's precision for all iterations has a very low standard deviation, suggesting that the procedure is accurate and that any selection bias is small.

We used accuracy, precision, and recall tests to see the effectiveness of our proposed model. The recall shows what number positive (Not-Depressed) correct cases were found, while the accuracy indicates how accurate the positive (Not-Depressed) correct predictor was. 15 participants were classified as depressed after taking the BDI-II questionnaire, while the remaining 15 weren't.

Table 1. SVM Depression Detection Confusion Matrix

		Expected	
		Feeling depressed	**Not Feeling depressed**
Actual	Feeling depressed	7	8
	Not Feeling depressed	5	10

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Table 2.Nave Bayes Depression Forecast Uncertainty Matrix

		Expected	
		Feeling depressed	**Not Feeling depressed**
Actual	Feeling depressed	4	11
	Not Feeling depressed	0	15

In the case of depression estimation, Table 1 shows the values for True Positive, True Negative, False Positive, and False Negative of the SVM classifier.

In depression prediction, The True Positive, True Negative, False Positive, and False Negative values

Table 3. Study of Similar Job Output Measures in Contrast

Name of Research	Exactness	Rigour	Recall
Depression Prediction Model based on SNS	77%	78%	85%
Predicting Depression via Social Media	69%	68%	62%
Proposed System	63.3%	100%	57%

of the Nave Bayes classifier are seen in Table 2.

To validate the scheme, we compare the proposed system's performance metrics to those of similar works in Table 3. While our proposed approach had the highest precision, it had the lowest accuracy and recall.

This research used the questions based on Stress, anxiety and depression as well to diagnose anxiety, depression, and stress. Data from 348 participants was collected using Google forms, and machine learning algorithms that were used to categorise the data are namely: Decision Tree, Random Forest Tree, Naive Bayes, Support Vector Machine, and KNN.

4.1 Questionnaires

The Depression, Anxiety, and Stress Scale questionnaire used to collect analytical data. DASS 21 was created with 21 questions, consisting of seven questions assigned to all three levels of stress, anxiety and depression.

The possible answers to the whole question, which may be represented on the text or the numerical form, are as follows:

0 was not applicable to me.
1 To some point, or at least some of the time, it may be said to be referring to me.
2 It happened to me in a big way or over an extended period of time.
3 This is something that happens to me a lot of the time, if not all of the time.

Table 4 lists the questions that were asked of individuals

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Table 4.

Revulsion	Depression	Stress
Mouth dehydration	It was difficult to be happy	It was impossible to rest
Breathing difficulties	It's difficult to summon the energy to get things done	Excessively respond to a scenario
Feel your body shaking	There is little to anticipate	A great deal of nervous capacity
They're concerned about panicking and humiliating themselves.	I was sad and depressed.	Become irritated
On the brink of hysteria	Enable people to be excited	It's impossible to unwind.
In the absence of physical exertion, mindful of heart action	I didn't feel like I was much of a human.	I was intolerant of not being allowed to do what I was doing.
I was terrified for no apparent cause.	I had the impression that life had no meaning.	Sensitive

Following data collection, the answers of the participants scores were estimated by adding the values associated with each query and using the formula below:

Table 5. Severity Levels

	Revulsion	Depression	Stress
Symptomatic	0-7	0-9	0-14
Slightly	8-9	1-13	15-18
Medium	10-14	14-20	19-25
Major	15-19	21-27	26-33
Extreme	20+	28+	33+

Score = total of each class's rating points * 2

Table 6. Encoded Values of the options

Options	Value
Never	0
Often	1
Most of the times	2
Everyday	3

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The final scores were classified according to severity – Average, Mild, Mild, Heavy, and Highly Severe – these were the classifications after they were assessed.(see Table 5).

The mark encoder will encrypt the four options in Table 6 whether the question is "Are you regular in school/college?" and there are four options.

Data is pre-processed before being used for training. The expanded version of the Patient Health Questionnaire is referred to as the prepared questionnaire. Questions such as email addresses and school/

Table 7. Labels for the students dataset based on their grades

Score	Depression Severity	Label/Stage
0-5	Minimum or nothing	0
5-13	Slightly	1
14-26	Medium	2
27-39	Major	3
>30	Extreme	4

college names that do not contribute to predicting depression phases are omitted from the questionnaire. Finally, using Label Encoder, which transforms categorical labels to numerical labels, scores are as-

Table 8. Labelling Data

Sr. No.	Features	Student 1	Student 2
1	How old are you?	2	2
2	Gender(M/F)	1	0
3	Do you attend school or college on a daily basis?	0	2
4	Are you sad or hopeless?	1	2
5	Insomnia, or sleeping excessively	1	3
6	Do you have a lot of stamina or are you tired?	1	2
7	Is it a case of overeating or a lack of appetite?	0	1
8	If you have a negative feeling about yourself?	1	3
9	Problems concentrating on tasks	1	2
10	Is it likely that you were driving or speaking slowly enough for someone to notice?	0	1
11	Have you ever considered that you'd be better off dead?	0	2
12	If you ever purposefully overdosed on drugs?	0	0
13	Have you ever been abused emotionally or mentally?	0	1
14	Do you have a sense of desire to do things?	1	2
15	What amount of the time do you spend on social media?	2	2
16	Do you tell your parents everything?	1	1

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signed to all of the choices based on how much they relate to depression. The depression stages are then classified based on the Table 7 displays the combined scores of each data entry to create a data package.

Assume the pre-processed data of two students is shown in Table 8 after converting the questionnaire's chosen choices to numbers Based on answers, each column in the processed data can now be labelled from 0 to 4 depending on the degree of depression.

5. CONCLUSION

In the last few years, we have witnessed a lot of research on application of Machine learning in dealing with mental health of humans. In this work, we began a project to find new ways to predict depression. by proposing an android application coupled with machine learning to predict depression level. Different algorithms are deployed for the same. Currently we are more focused on creating an user friendly and accurate prediction application which would lead to an accurate and desired output. Epigenetic research on mental wellbeing and ill-health is exploding, and it will undoubtedly make a major contribution to our understanding of aetiology in the coming years. If that's the case, it may also better clarify how conventional pharmacological and psychotherapeutic treatments for mental disorders work, or suggest new approaches that may be more effective.

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Chapter 7
Automated ICD Coding Using Deep Learning

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ABSTRACT

ICD (international classification of diseases) is a system developed by the WHO in which every unique diagnosis and procedure has a unique code. It provides a standardized way to represent medical information and makes it sharable and comparable across different hospitals and countries. Currently, the task of assigning ICD codes to patient discharge summaries is performed manually by medical coders. Manual coding is costly, time consuming, and inefficient for huge data. So, the healthcare industry requires automated solutions to make the medical coding more efficient, accurate, and consistent. In this study, the automated ICD-9 coding is approached as a multi-label text classification problem. A deep learning system is presented to assign ICD-9 codes automatically to the patient discharge summaries. Convolutional neural networks and word2vec model are combined to automatically extract features from the input text. The best model has achieved 83.28% accuracy. The results of this research prove the usability of deep learning for multi-label text classification and medical coding.

INTRODUCTION

ICD (International Classification of Diseases) is a system created by WHO for assigning every unique diagnosis a unique code. It is used by hospitals and other healthcare providers for classifying all the procedures, symptoms, and diagnoses recorded in various clinical events. ICD provides a standardized way to represent medical information such as diseases and medical procedures to make it shareable and comparable across different countries as well as hospitals. It also enables uniformity among doctors in recording clinical data for research purposes and reimbursement claims. It facilitates easy storage,

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analysis, and retrieval of health information for evidence-based decision-making. Usually, ICD codes are assigned to a medical record by the medical coders according to the clinical notes written by the doctor. These coders must have specialized skills such as coding rules, knowledge of medicines, and medical terminologies. Manual coding is very expensive, time-consuming, and inefficient for a huge amount of data. According to a study, only 60% to 80% of the assigned ICD-9 codes reflect actual patient diagnoses in the discharge summaries. Hence, it is necessary to develop an automated system for assigning ICD codes to patients' discharge summaries. The objective of this chapter is to propose a solution to this problem using deep learning.

BACKGROUND

A patient can have multiple diagnoses, i.e. multiple ICD codes. So, a discharge summary can be seen as an instance that can have multiple ICD-9 codes (labels) and the number of correct labels for that discharge summary is unknown. So, we can define the problem of automated ICD coding as a multi-label classification problem. There is a uniqueness in this problem. Due to the hierarchical structure of the ICD tree, some ICD codes are mutually exclusive while some codes are related to each other. Also, some diseases are extremely rare and some are very common, so label distribution is highly skewed.

We will go through some concepts which are addressed in this chapter.

1. ICD-9 CODES

ICD-9 code is a 5 digit alpha-numeric code that describes a unique diagnosis or procedure. The first three digits of an ICD-9 code make up an ICD-9 category. Thus, to make the ICD-9 category identifiable, a decimal point is given after the third digit of the ICD-9 code. For example, 001 is an ICD-9 category whose description is 'cholera', and 001.1 is an ICD-9 code, whose description is 'cholera due to vibrio cholerae'. The ICD-9 system has a hierarchical structure. So, more specific ICD-9 codes have more digits in them. An example of the ICD-9 code hierarchy is shown in figure 1.

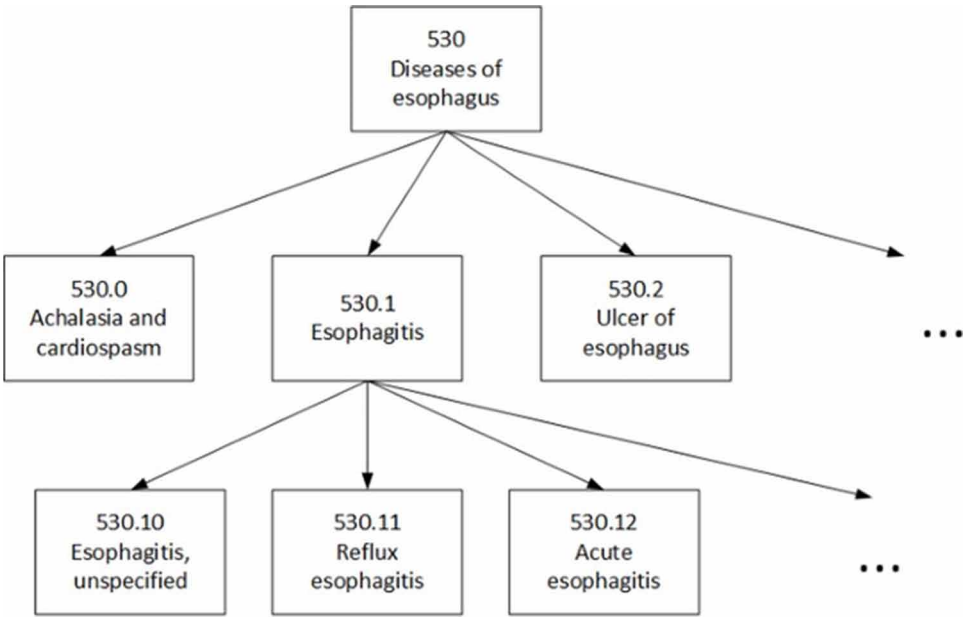
2. MULTI-LABEL TEXT CLASSIFICATION

Multi-label classification is often misinterpreted as multi-class classification. Multi-class classification means a classification task in which there are more than two classes and each of them is mutually exclusive. An instance can have only one class among these multiple classes. On the other hand, in Multi-label classification, each instance can be assigned with a set of target labels. Here, an instance can be associated with any number of labels among the target labels.

Multi-label text classification can be supervised or unsupervised. For this problem, authors have predefined labels (ICD codes). So, the focus of this chapter will be on supervised classification. Authors provide labeled data to the machine learning algorithm as the input. The algorithm gets trained on the labeled dataset and gives the desired output (set of labels for each instance). During the testing phase, the algorithm is given completely new data without any labels. The algorithm then classifies that data into categories based on the knowledge it acquired during its training phase.

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Figure 1. ICD-9 sample subtree



3. DEEP LEARNING

Deep learning is a faculty of machine learning which deals with simulating the learning approach used by any human being to acquire knowledge. Traditional machine learning algorithms which are also called shallow learning algorithms are linear whereas deep learning algorithms are hierarchical combinations of layers with increasing complexity. These algorithms are also called artificial neural networks (ANN). There are many types of neural networks, we will study RNN and CNN in detail.

3.1 Recurrent Neural Networks (RNN)

RNN is a type of artificial neural network which has a directed cycle. It facilitates information retaining. Random sections of data can be processed by them using their internal memory. We can think of a recurrent neural network as multiple replicas of one network, in which each node transfers data to its successor. A recurrent neural network (RNN) can process a text input with any number of words by applying a transition function recursively to its internal hidden state vector induced from the input text.

3.2 Convolutional Neural Networks (CNN)

It is a type of feed-forward and deep neural networks, that are mostly applied to computer vision. Multilayer perceptrons that are specially designed to require minimal preprocessing are used in CNN. We can think of convolution as a sliding window function is applied to a matrix. The sliding window in this context is called a feature detector, kernel, or filter. CNN is composed of convolution layers with nonlinear functions of activation applied to the results. In the training phase, this classifier learns the values of its kernels based on the task assigned to it automatically. The important advantage of CNN is that it

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can detect local features from images automatically. Automated ICD coding is a text classification task for which local context features extracted from medical terminologies are very important.

4. WORD2VEC

Word2vec is a set of models that are used to convert words into word embeddings. These models are neural networks with 2 layers. They are trained to build the contexts of words. The input to word2vec is a large text corpus and the output is a vector space. Each unique word in the corpus has its own vector. Words that have the same contexts in the corpus are located closer in the vector space. The quality of word embeddings mainly depends upon the corpus on which the word2vec model is trained. The authors have used word2vec to build a vector matrix for each input document which is the input to the classifier.

Related Work

There have been many research projects carried out on the ICD coding automation since the year 1990. Recently, many researchers have applied machine learning algorithms for this task such as Naive Bayes, k-nearest neighbors and Support Vector Machines (SVM), and other methods based on Natural Language Processing (NLP). There are also some research projects in which deep learning is used for automatic ICD-9 coding. Ruch et al. (2008) combined machine learning methods such as (k-nearest neighbors) with data-poor methods for text classification. They reported that the performance of the data-poor methods was low and they improved the results by the use of temporal features. This combined system achieved a top-20 recall of 63%. Chen et al. (2010) incorporated a deep semantic analysis approach along with dependency parsing and parse tree matching. They evaluated their model using semantic matching scores. Pereira et al. (2013) proposed a text mining approach based on k-nearest neighbors for children epilepsy classification according to ICD-9 standard. Perotte et al. (2013) developed two SVM classifiers for ICD-9 code assignment, one is a flat classifier and the other is a hierarchical classifier. The hierarchical classifier uses the hierarchical structure of the ICD-9 tree in classification while the flat classifier treats each ICD-9 code as an independent label. The hierarchy-based classifier achieved F-measures of 39.5% while the flat classifier achieved an F-measure of 27.6%. They also proposed a new evaluation metric 'shared path' to measure the performance of their SVM classifiers.

OVERVIEW

Authors have approached the problem of automated ICD-9 coding problem as a multi-label classification problem. There are two main parts of this system: the first is vector generation and the second is multi-label classification. For the vector generation, the authors have used a pre-trained word2vec model. This word2vec model is trained on a huge collection of PubMed and PMC articles. The second part of this system, multi-label classification is the part where the actual assigning of ICD codes to the patients' discharge summaries takes place. The authors have used the convolutional neural network model for this multi-label classification task. The output of the first part, vector generation, is used as the input to this CNN model. The model then returns the list containing the prediction probabilities of each code for a

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given patient visit. Finally, an ICD code is assigned to a given patient visit if its prediction probability is greater than a predefined threshold value.

Issues, Controversies, Problems

The task of automating the ICD-9 coding of discharge summaries has the following challenges:

1. A discharge summary is an unstructured text document written by a doctor or hospital staff in his/her own style. So, it's difficult to extract relevant data from these discharge summaries effectively.
2. While writing discharge summaries, doctors use a lot of medical terminologies and abbreviations. So, it becomes difficult to capture semantic information from these discharge summaries.
3. There are many ways to describe a disease name. Also, there is not always a one-to-one mapping between diagnosis phrases in the discharge summary and ICD codes assigned to that discharge summary.

SOLUTIONS AND RECOMMENDATIONS

Dataset Preparation

1. Overview of MIMIC-III

The authors have used the MIMIC-III (Johnson et al., 2016) dataset for this research. MIMIC (Medical Information Mart for Intensive Care) is a huge database that contains data related to the patients who were admitted to critical care units at a large hospital. It is the only freely accessible critical care database available for this task.

Before training the model, it is crucial to understand the distribution of data labels. On average, a patient has 13.9 labels. This dataset has a total of 6985 ICD codes, with an unbalanced distribution. 50% of the labels in the dataset are made up of the top 105 codes. 1503 labels have just one example in the whole dataset and for 3110 labels, there are less than 5 examples in the dataset. In the MIMIC-III dataset, the longest record contains 7,980 words and the shortest one has only 9 words.

2. Data Preprocessing

The authors have used the 'noteevents' table in the MIMIC-III dataset which contains clinical notes for each patient visit. For the classification task, they used the notes with the category 'discharge' and the description 'summary'. There isn't any fixed format for writing a discharge summary. There are not standardized sections. For example, in some notes, there is a discharge diagnosis section whereas in other notes there is a final diagnosis section. So, the authors thoroughly examined the data to extract the necessary information correctly. Then they performed the following operations on the text:

1. Removed numbers, bullets, dates, and names from the text Created tokens by combining frequently co-occurring words

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Then, they created 3 types of datasets for classification experiments:

1. Dataset of Diagnosis sections of all patient visits
2. Dataset of entire discharge summary of all patients
3. Dataset containing a list of medical terms extracted from each discharge summary

Table 1. Basic statistics of MIMIC-III

Statistic	Count	Statistic	Count
Number of discharge summaries	52962	Total number of codes	6984
Average word count per record	1524	Average no. of codes per patient visit	11
Maximum no. of words per record	7980	Maximum no. of codes per patient visit	39
Minimum no. of words per record	9	Minimum no. of codes per patient visit	1

'Discharge Diagnosis' section is the most relevant section in a discharge summary for this task. It contains a list of diagnoses given by the doctor for a patient visit. But it's not the only section that has relevant information for this task. The remaining discharge summary has lots of unstructured text and the proportion of relevant data in this text is very small. First, the authors prepared two models, one trained on diagnosis sections and the other trained on entire discharge summaries. The results were not satisfactory so they created a dataset of medical terms extracted from discharge summaries. While extracting medical terms from the discharge summary, they had to perform negation detection and abbreviation expansion. For that, they used UMLS (Unified Medical Language System), which is a compilation of various vocabularies in the biomedical field. ICD-9 code has 5 digits. The first 3 digits of an ICD-9 code make up an ICD-9 category. They converted all ICD-9 codes in the dataset into ICD-9 categories due to insufficient data and some resource constraints. There are 842 ICD-9 categories in the MIMIC-III dataset.

Components of the System

1. Word Embedding

The quality of word embeddings is directly related to the corpus on which the word2vec model is trained. There are various pre-trained word2vec models available that are trained on a large corpus such as Google News and Wikipedia. But, they are trained on a generic corpus, which limits their direct use for biomedical text classification. The authors have used the word2vec model which is trained on PubMed and PMC articles. The articles in PubMed and PMC make up a huge knowledge base in the biomedical domain. That's why they used the word2vec model trained on these articles for this task. This model converts each input word to a 200-dimensional vector.

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2. Classifier

Authors have used CNN classifier to predict ICD-9 codes of discharge summaries. CNN uses layers containing convolution filters. These filters extract local features. So, the network automatically learns the features whereas in traditional algorithms they have to be hand-engineered. In this task, local features can be seen as phrase-level features for a given discharge summary. First, the authors converted every word in each document into a low-dimensional vector using the word2vec model to create a document matrix for that document. This document matrix is then provided as the input to the CNN model. CNN ignores the input text's semantic features because it doesn't consider the word order. The word count in a discharge summary varies by a large amount, but the CNN model only takes a fixed-sized matrix as input. So, if a document has more words than the predefined length, the document is truncated and if it has a lesser number of words then it is padded by zeros. So, if the variance in the length of each document is huge, the performance of this model can get affected.

The authors used the n-gram approach for classifying the input text. There are three convolution layers in this model, each followed by a relu activation layer and a max-pooling layer. The authors preferred relu over tanh because relu overcomes the gradient vanishing problem. They chose kernel sizes of 1, 2, and 3 for layer-1, layer-2, and layer-3 respectively. A kernel with size k takes k-word vectors as input and produces a feature vector as output. If k=1, pool size equals the number of words in the input text. If k=2, pool size equals the total number of words minus one and so on. The max-pooling layer then extracts features with maximum activation (i.e. the most relevant words in the document for classification).

To regularize the model and prevent overfitting, a dropout layer with a dropout rate of 0.5 is added after the last pooling layer. Then a flattening layer is added which takes the previous layer's output and flattens the structure of it to create a single feature vector which is used by the fully connected layer for the classification. Finally, a sigmoid activation function is used in the final dense layer. Authors preferred sigmoid over softmax because the softmax function is good for multi-class classification where each instance can have only one label, and not for multi-label classification. Softmax sums up the output probabilities to one, which makes sense only when there is only one class for any instance. The sigmoid layer outputs the probability for each class, which is between 0 and 1, independently. The authors used binary cross-entropy as a loss function. Authors preferred binary cross-entropy over categorical cross-entropy because categorical cross-entropy works for multi-class classification and not for multi-label classification. They have used adam optimizer for gradient descent optimization.

Workflow

The workflow of this system has three basic phases: data preprocessing, training and testing. These phases are thoroughly explained using figures 2,3 and 4. Authors have also developed a user-friendly web application for classifying discharge summaries into ICD-9 codes. Its workflow is explained in figure 5.

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Figure 2. Data Preprocessing

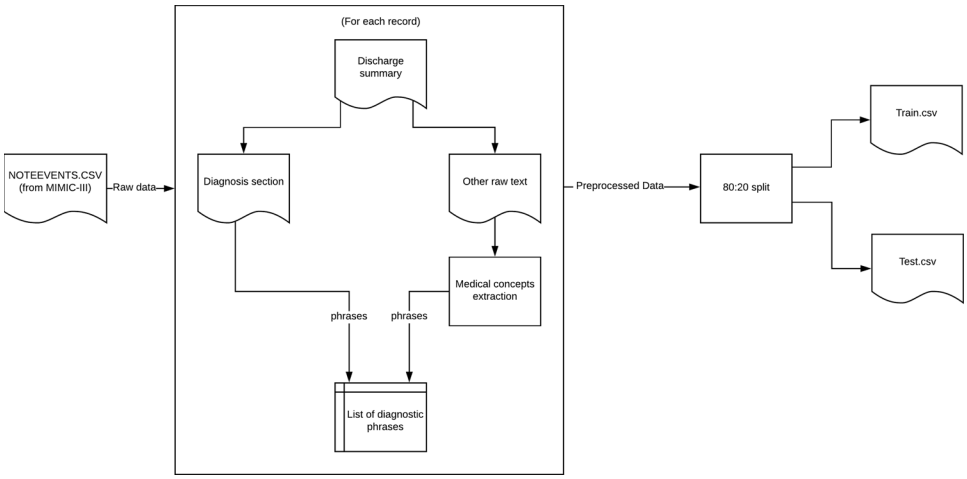


Figure 3. Classifier Training

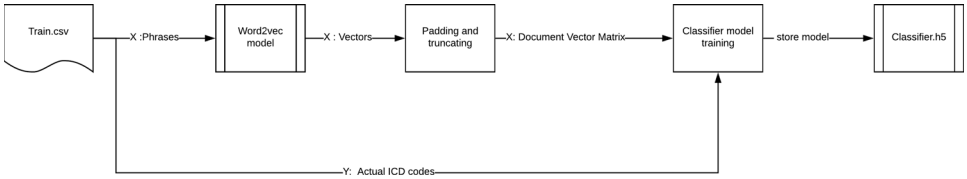
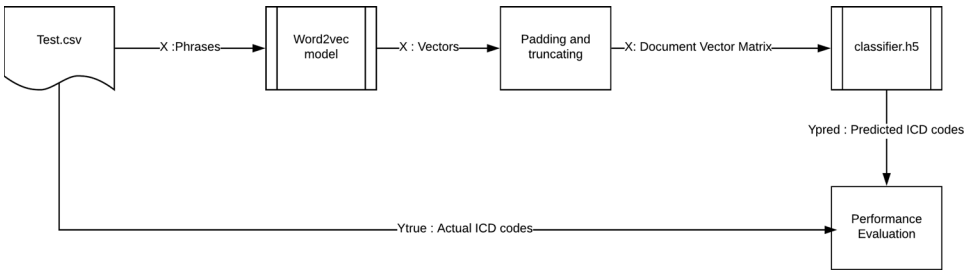


Figure 4.Classifier Testing



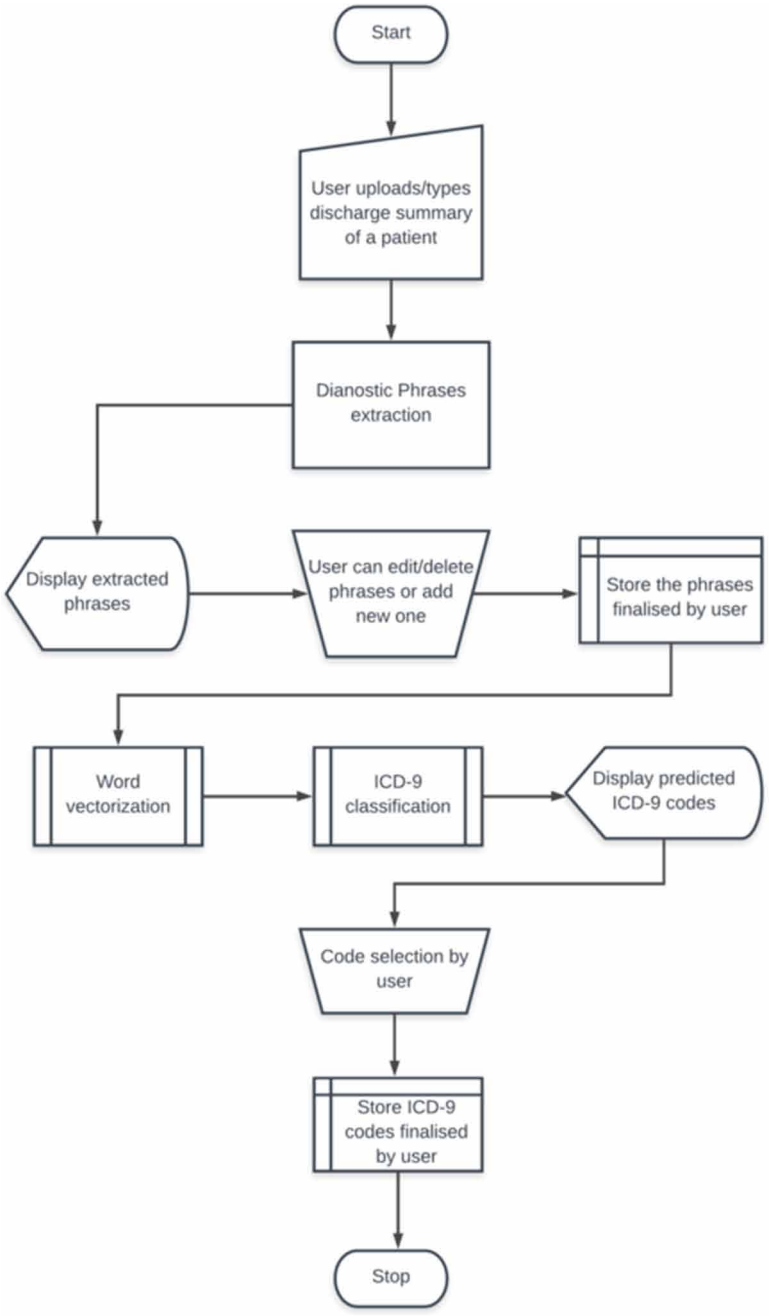
Result Analysis

Table 2 indicates the performances of CNN models trained on different types of input data. Here, the recall of the diagnosis section model is less than the recall of the discharge summary model while its precision is greater than the precision of the discharge summary model. It indicates that the diagnosis section is more pertinent than the remaining discharge summary, but it alone is not enough to retrieve all ICD codes of a patient visit. The remaining discharge summary has lots of unstructured text and a small portion of it is relevant to this task. Also, the number of words in the discharge summary varies in a huge amount, which leads to more truncating and padding which affects model performance. So,

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the discharge summary model doesn't have significant performance improvement over the diagnosis section model. The third model, which has been trained on the list of medical terms extracted from the entire discharge summary, has far better performance than the previous two models.

Figure 5. End User Application



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Table 2. Performances of different CNN models trained on different types of data

Model Type	Precision	Recall	F1-score	Top35 accuracy
Diagnosis section	50.09%	44.51%	47.13%	74.36%
Entire discharge Summary (raw text)	48.80%	45.99%	47.35%	75.37%
Medical terms in discharge summary	60.4%	52.32%	56.07%	83.28%

Another factor that affects the model performance is label frequency in the training set. To observe how label-frequencies affect the model performance, the Authors calculated F1-scores for each label separately. Figure 6 shows the graph plots of label-wise F1-scores versus label frequencies in the training set.

According to these graph plots, the F1-score is pretty much affected by the label frequencies. For the codes that have frequencies less than 2000, the F1 score varies between 0 to 80%. The codes that have frequencies between 2000 and 4000 have F1 scores between 10% and 90%. For the codes with frequencies more than 4000, F1 scores are more than 60%. The graph for codes with frequencies less than 2000 is very dense while the other two graphs are sparse. It means that most of the codes in the dataset have a low frequency. It proves that the model performance will improve when a sufficient amount of training examples will be available for each ICD code.

Comparison with Previous Research Work

Table 3 shows the results of some previous research projects along with classification algorithms and the number of ICD-9 codes they have used for classification and Table 4 shows results of previous projects in which ICD-9 categories are used for classification. The author's model classifies discharge summaries into ICD-9 categories with an F1 score of 56.07, which is greater than all of the F1 scores mentioned below.

Table 3. Projects where notes were classified into ICD-9 codes

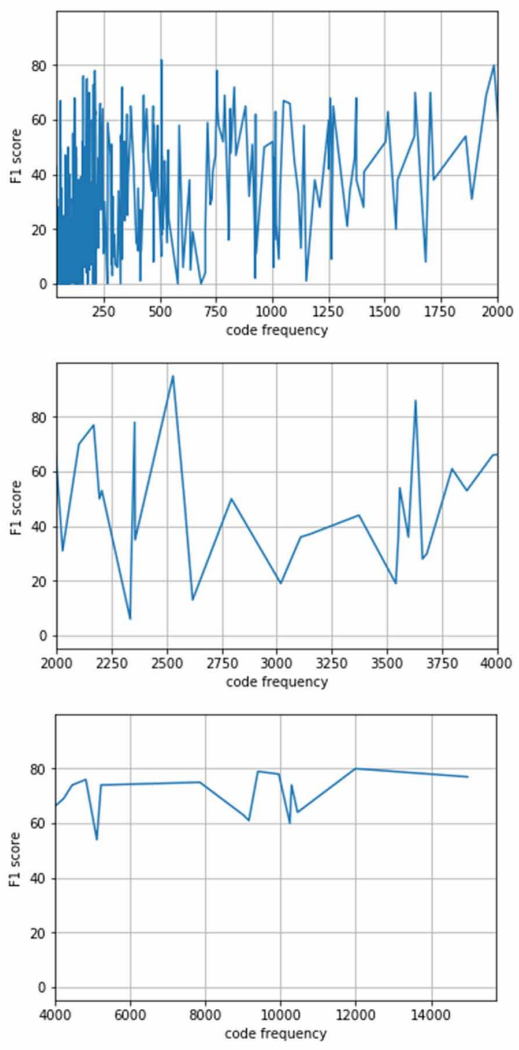
Research Project Reference	Machine learning algorithm used	Number of ICD-9 codes used	F1-score (in %)
Shi et al. (2017)	LSTM	50	53
Nigam (2016)	RNN	100	24
Perotte et al. (2013)	SVM	5000	27.6

Table 4. Projects where notes were classified into ICD-9 categories

Reference	Machine learning algorithm used	F1-score (in %)
Baumel et al. (2017)	CNN	52.64
Baumel et al. (2017)	HA-GRU	55.86

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Figure 6. Graph plots of label-wise F1 scores Vs Label frequencies in the training set



FUTURE RESEARCH DIRECTIONS

Due to insufficient training data and constraints imposed by resources such as RAM and processing power, authors classified discharge summaries into 3-digit ICD categories and not into full 5-digit ICD codes. But this classification model can easily be extended for 5-digit ICD codes when sufficient data and resources will be available. In the future, lab tests and medications of the patients can also be used along with the discharge summaries to predict ICD codes. WHO had completed the development of the 10th revision of ICD, ICD-10 in 1992 which went into effect in the USA from the year 2015. Due to the unavailability of a freely accessible dataset for ICD-10, authors have used ICD-9 for this research. One can easily adapt to ICD-10 once such a dataset is available.

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CONCLUSION

In this research, the authors have developed a system that combined CNN with a word embedding system for the assignment of ICD- 9 codes to patients' discharge summaries. The advantage of this system is that it can extract features automatically from the input text. Due to various limitations of the MIMIC-III dataset, many researchers have used only a few ICD codes that occur most frequently in the dataset for classification. Lesser the number of labels used for classification, lower is the complexity of the trained model. It may improve the accuracy of the model, but it reduces the usability of the system in real-world applications. For example, the classifier model with 80% accuracy which classifies the discharge summary into only 10 ICD codes is as useless as the model with 20% accuracy which classifies the discharge summary into all possible ICD codes. We need to achieve equilibrium between the number of ICD codes used for classification and the accuracy of the classifier in order to obtain a classification model that can be used in real-world applications. The best model in this research has achieved 83.28% top-35 accuracy which proves its real-world usability.

ACKNOWLEDGMENT

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Chapter 8
Autonomous Smart Device for COVID-19 Detection Using Artificial Intelligence

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ABSTRACT

Corona is a pandemic disease and is spreading all over the world. There is also lack of corona virus detection machines. If it is detected at very early stages without pathological intervention, then further spreading of the disease can be controlled, and many of human lives can be saved. So, the proposed biomedical device can be used for fast and accurate prediction of COVID-19 from chest x-rays. X-ray can also be taken from anywhere and sent through any communication medium. Even if error is added, it can be removed using error concealment algorithms. Automated AI-based systems will be used for prediction of normal, COVID-19, and pneumonic cases from x-ray images. It makes detection of COVID-19 infection less costly and portable. This device can be stored in less stringent conditions, making it more effective.

INTRODUCTION

Ten years after the 2009 influenza pandemic, the world is witnessing an even more crippling pandemic, now called the 'Covid-2019'. The ICTV has named the virus causing this pneumonia-like disease as "SARS-CoV-2" (Severe Acute Respiratory Syndrome- Corona Virus 2). These were followed by more imported cases via Italian tourists, and their suspected contacts in India. The virus is known to have an extremely contagious nature and because of the shortage of medical kits and equipment, researchers started finding different methods for detection of covid-19 (Khan et al., 2021; Kumar et al., 2020). Radiology images such as X-ray can also be used for detection of Covid-19, which is more effective

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than the measurement of body temperature of the individuals also known as the thermal screening of the body. The worst affected organs identified in Covid-19 patients is notably the respiratory system thus the usage of chest radiology images for the detection of the virus can be very effective (Chamola et al., 2020; Rajaraman et al., 2020).

Around November 2019, there were reports of an outbreak of unexplained pneumonia, with majority of the cases reported around China's Seafood Wholesale Market, where they sold live fish, poultry, and birds. corona virus was officially detected in January 2020 by Chinese officials. It started spreading throughout the world.

The world has been under a turmoil lately for the lack of awareness and the underlying uncertainty that lies at the heart of this recent pandemic. Scientists all over the world are struggling to come up with new ideas to ease the requirement of frontline workers and especially finding a one-and-all solution to the dreaded viral disease of Covid-19 (Chen et al., 2020). The detection of the virus is an extremely slow procedure because it takes around 3 to 14 days for the complete set of probable symptoms to show up. Many of the reports have shown people to be asymptomatic wherein the person usually experiences no symptoms but is an effective propagator of the deadly virus if gone unchecked. Fever, breath shortness, cough etc are the initial symptoms of Covid-19. Thus, transmission may also occur indirectly through touching surfaces in the immediate surroundings. The project mentioned in the paper is one such step toward achieving the need of the hour. Before treatment of any sort can be prescribed to a patient, early and accurate detection of the disease is very crucial before any devastating event happens. Artificial Intelligence (AI) could be trained to detect and different the Covid-19 affected patients from normal pneumatic patients by analyzing the medical images and the underlying characteristics of an affected patient's lungs (Zhang et al., 2020). Thus, a revolutionary technology of AI could be used for the betterment of the current situation of Covid-19 all over the world (Shi et al., 2020). Artificial Intelligence is taken into consideration as a rising opportunity within technology of the Internet and digital world. Many nations are enhancing AI to take a look at COVID-19 infections, tell healthcare systems, and installation speedy movements to control it unfold. Different artificial intelligent technology can be used to handle Covid-19(Khan et al., 2021)[3].

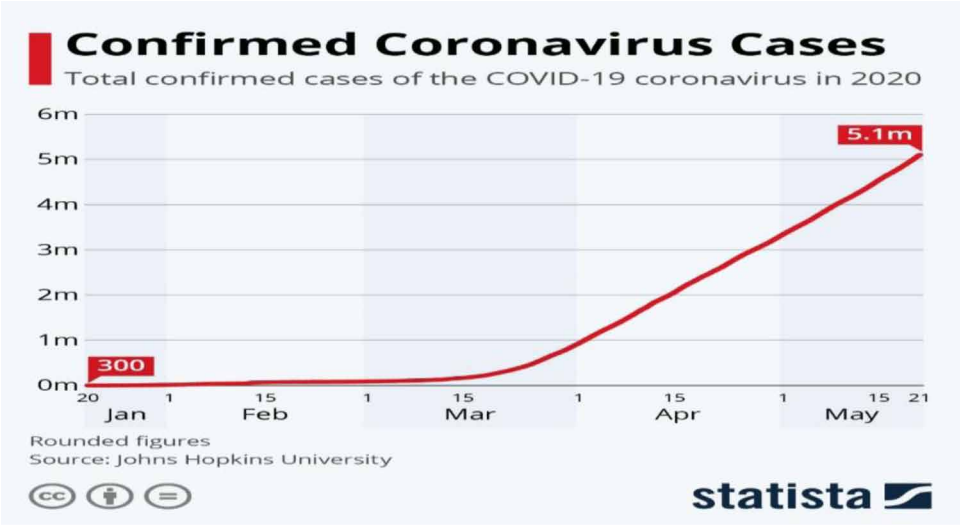
MOTIVATION

Covid-19 is a pandemic disease and is widely spreading all over the world. There is also a lack of corona virus detection machines. If it is detected at very early stages without pathological intervention. Also, X-ray can be taken from anywhere and can send through any communication medium. The fast and accurate detection of COVID-19 can help in further spreading of the disease. Thus, it can be controlled and many human lives can be saved (Chamola et al., 2020)[5].

Unfortunately, as no effective therapeutic drug is yet available, the infection will continue to spread until the population acquires sufficient herd immunity or an effective vaccine becomes available. The respiratory system especially lungs is identified to be the part of the human body which is more affected by the corona virus. Thus, upper body of the chest image will be more efficient than thermal scanning (Khan et al., 2021; Kumar et al., 2020). In thermal scanning, the individual person's body temperature is measured. Due to improvements in algorithms considerable improvement in Image Recognition has been achieved over the years. Image Recognition and classification have gained momentous appreciation due

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Figure 1. Statistics showing the identified cases of Covid- 19 as of May 2020



to applications of concepts such as Convolution Neural Networks (CNN) and methods such as transfer learning (Albawi et al., 2017; Anthimopoulos et al., 2016; Rajaraman et al., 2020; Shen et al., 2017).

Since April 2020, widespread adoption of screening methods and the use of chemical-based tests such as RTPCR tests for the detection of coronavirus disease have been widely popularized by the World Health Organization (WHO) (Lei et al., 2020; Shi et al., 2020). The current situation has become a hotbed for research related activities in improved methods of detection of the disease which might help the scientific community and also the general public for immediate identification and containment of the virus as soon as possible.

Table 1. Various tests available for Covid-19 (Kumar et al., 2020)

Test Types	Advantages	Disadvantages
RT-PCR (48-hour results)	Specific, very sensitive	It may take some days to get the results.
Antigen (15-minute results)	Fast results, very specific, more sensitive to positive results.	Less reliable for negative tests than PCR; less effective later in disease
Antibody (Within 24 hours results)	Serology test in which the blood sample is tested	Research field; not many people develop antibodies if they are affected.

The popular tests employed for Covid-19 detection are antibody tests and viral tests. Molecular RT PCR and rapid antigen tests (RAT) indicates a current infection. Whereas the antibody test usually gives information about a previous infection. Antigen tests can provide results within 20 to 30 minutes while the PCR test takes 12 to 24 hours (or longer) for turnaround. As is obvious, lot of laboratory and professional equipment is required to carry out these tests and it definitely adds to medical expenditure to a great extent.

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Table 2. Various Covid-19 Diagnosis Methods (Kumar et al., 2020)

Various Methods	Working principle	Advantage	Time required	Disadvantage
NGS (Next generation sequencing)	Whole genome sequencing	• Very sensitive and specific • Provide all related information • Can identify novel strain	1–2 day	• Very much expertise • Equipment dependency and high cost • More sophisticated Lab is needed
RT-PCR	Specific primer-probe based detection	• Results are faster • More sensitivity • Needs small amount of DNA • Can be performed in a single step • Well established methodology in viral diagnostics	3-24h	• Costs is more due to expensive consumables • Lab equipment very much costly • Detection is very complex • Detection will take a lot of time.
Serological (traditional)	Antigen/Antibodies IgG/IgM	• Sensitive and specific	4-6h	• Testing come after 3-4 days of infection • False positive
Rapid serological	Antigen/Antibodies IgG/IgM	• POCT	15-30min	• Testing come after 3-4 days of infection • False positive
CT scan	Chest images	• Enhance sensitivity of detection if findings combined with RT-PCR results	1h	• Indistinguishability from other viral pneumonia and the hysteresis of abnormal CT

From the Table2, it clearly understands the CT scan takes comparatively very less time, accurate results and no pathological intervention is needed. The HRCT (High Resolution Computed Tomography) test creates a detailed image of the lung anatomy and the airflow through it. This can be used to visually assess the lung anatomy and airflow patterns to detect and diagnose the underlying health conditions. The health department has admitted that mutated variants of the coronavirus were capable of dodging RT PCR tests. Thus, recommending that those with Covid-19 symptoms should undergo HRCT even if they test negative in RT PCR test. So, the most preferred way of testing the COVID-19 infection so far is using CT scan (Kumar et al., 2020)[6](Anthimopoulos et al., 2016).

Thus, proposed biomedical device can be used for fast and accurate prediction of Covid-19 chest X-rays. Moreover, X-ray can be taken anywhere and can be sent through any communication medium. Even if error is added, it can be removed using various Error concealment algorithms. Automated AI based system will be used for prediction of normal, Covid and pneumonia cases from each of the radiology images. Besides, it makes detection of Covid-19 infection inexpensive and quite portable. The device can be stored in less stringent conditions, making it more effective.

LITERATURE SURVEY

After an extensive research, some of the journal papers proved to be valuable resources for the development of the project. The extensive outbreak of the COVID-19 has encouraged a lot of scientists, researchers, laboratories, and organizations of the entire world to conduct a lot of research to faster and accurate treatment and vaccine development.

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Table 3. Literature Survey

Sr. No.	Title of the Paper	Year of Publication	Publisher	Methodology	Conclusion
1	Smart technologies driven approaches to tackle COVID-19 pandemic: a review.	2021	Biotech.	It explains the smart technology which is used for COVID-19 in area of drone, robotics, AI, mask, and sensor technology	The advantages and disadvantages analysis of smart technology for COVID-19 is discussed. This helps in understanding the affect of the technology on the society (Khan et al., 2021)
2	Weakly Supervised Deep Learning for COVID-19 Infection Detection and Classification from CT Images.	2020	IEEE	This paper makes use of deep learning to identify the potential characteristics of an affected patient's lungs and then accordingly detects the severity of the disease.	Concept of a supervised learning model can be employed from this idea.
3	A Comprehensive Review of the COVID-19 Pandemic and the Role of IoT, Drones, AI, Blockchain, and 5G in Managing its Impact.	2020	IEEE	This paper discusses the emerging technology to combat the threats posed by the virus. The current age of technology has helped us overcome the obstacles to some extent.	New age technology like AI and machine learning can be employed to ease the workload of many frontline workers.
4	Iteratively Pruned Deep Learning Ensembles for COVID-19 Detection in Chest X-Rays.	2020	IEEE	It focuses on the technicalities as to how the lungs are affected in a patient and collected data is later put to use for the early detection of the virus.	The image processing details and the collection of medical data can be put to use from this paper.

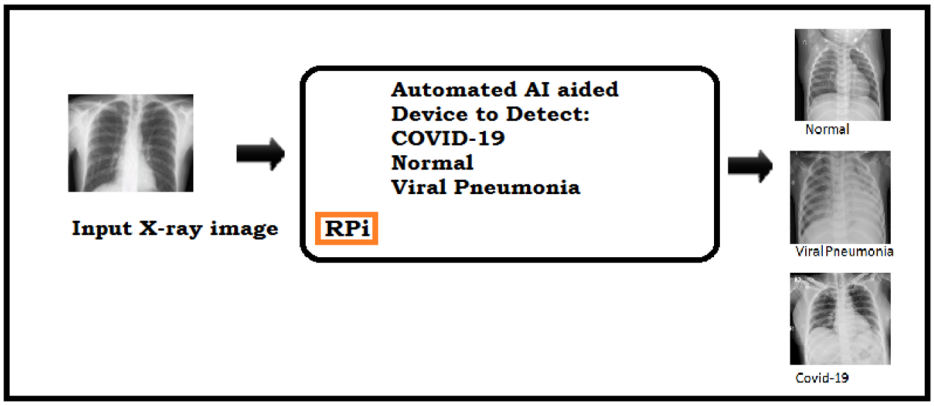
The above-mentioned papers () give a valid insight into the development of the research work that has to be carried out. The advantages and disadvantages analysis of smart technology for COVID-19 its impact is discussed in the first paper. Detection and classification using Supervised learning approach is discussed in the second paper. Review of Covid situation and the impact of different latest technology is explained in third paper. Deep learning concept is applied in Chest X-ray images for detection of covid-19. Along with these papers, the Concept of Error Detection and Concealment is also studied which is in the refence list of this papers (Rajani & Khaparde, 2017)[10](Rajani & Khaparde, 2016b). During the transmission of the X-ray images, errors can get added. These can be detected using the correlation concepts. The concealment of the X-ray error image can be done using Error Concealment algorithms such as Frequency Selective Extrapolation (FSE) algorithms (Rajani & Khaparde, 2016a). Once the concealment is done, the prediction of the covid can be done.

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METHODOLOGY

The overview of the proposed research is shown below. First, the Chest X-ray image is taken as input to the system. If any is detected for the x-ray image during transmission, the error concealment is done. This quality medical image will help diagnosis in a better way.

Figure 2. Overview of Proposed Research



The following diagram shows the actual block diagram of the proposed research. While transmitting the image some error can be added, so error concealment can be done initially. Then the pre-processing of the X-ray image is done. After that data augmentation is applied on it. After pre-loading the trained model, the training can be given with the help of Artificial Intelligent based algorithms. The training is given for prediction of Normal,COVID-19and Pneumonic cases. This trained system can be used for further classification of real time data. Thus finally from the given X-ray image, the prediction can be done for normal, pneumonia or COVID-19.

The most discriminating and prominent features for Covid-19 and severe pneumonia include peripheral distribution (80% in Covid vs. 57% in pneumonia), Ground Glass Opacity (91% in Covid vs. 68% in pneumonia) and vascular thickening (59% in Covid vs. 22% in pneumonia). These characteristic symptoms are extremely helpful in distinguishing between the two medical conditions.

The medical image of a 58 year old woman below clearly shows the increasing peripheral distribution of pus, GGO (Ground Glass Opacity) and vascular thickening as shown by the arrows.

Elements of Block Diagram

The main building blocks of the proposed research work are:

1. Error detection in the medical image(X-ray) during transmission
2. Error Concealment for the errored medical image(X-ray)
3. Detection of Covid-19 or not (normal or pneumonic)

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Figure 3. Block Diagram

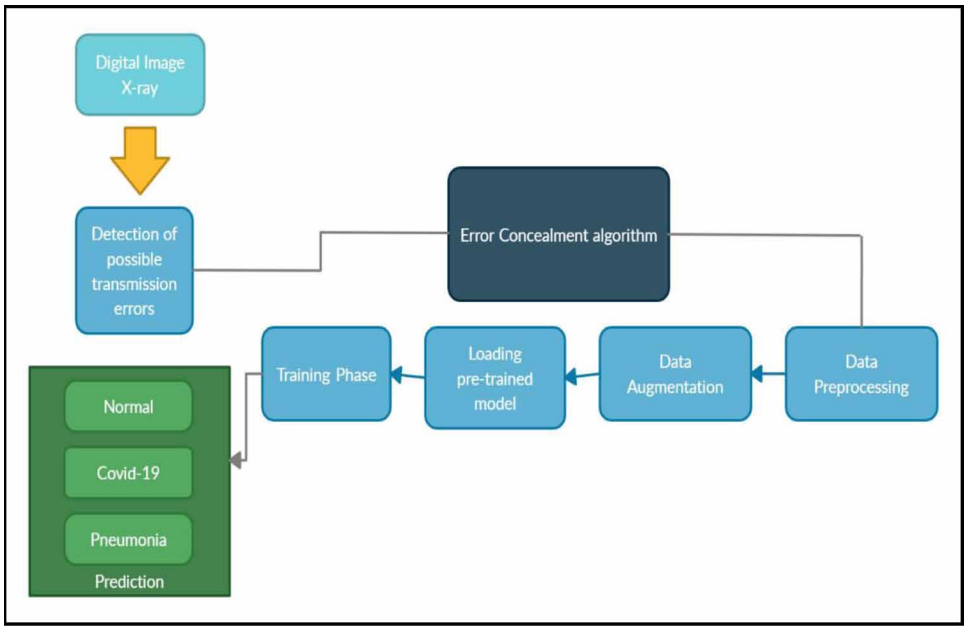
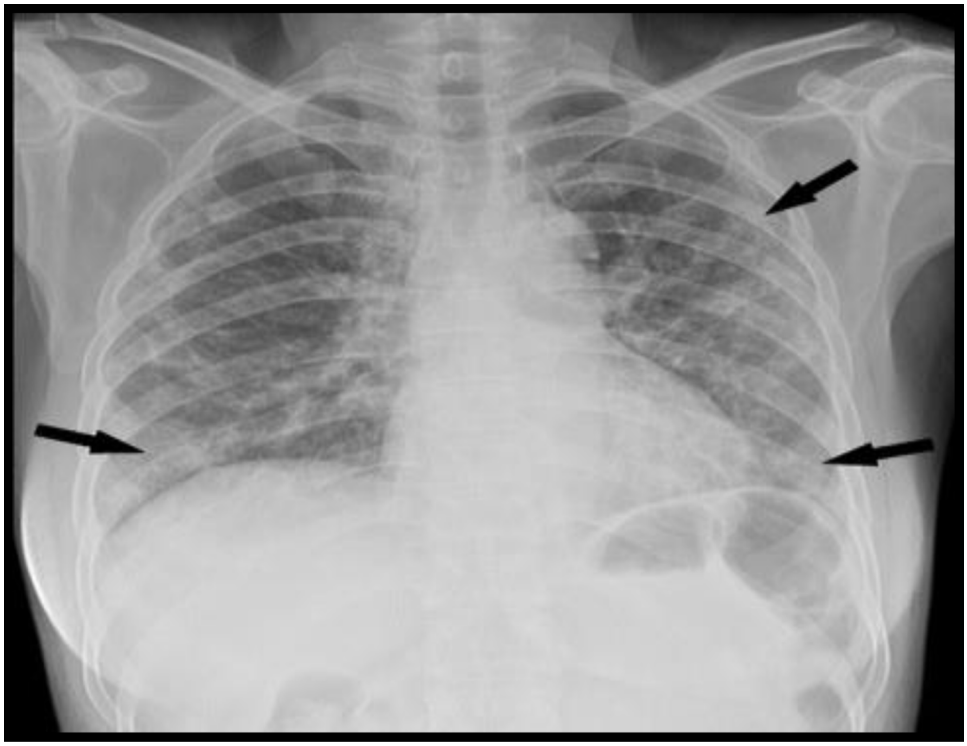


Figure 4. Medical image of a 58-year-old woman suffering from Covid-19.



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The digital image X-ray is analyzed initially for all the possible errors that might have occurred during the transmission of the image (X-ray). Once the errors are detected using suitable algorithms, the raw image is passed on to the error concealment phase of the project that uses Frequency Selective Extrapolation algorithm. The rectified image then serves as the dataset for the ML algorithm which executes to determine whether the image is that of a Covid patient or of a normal pneumonia affected patient.

The complete image dataset required for this research includes 2,906 radiology images of 1345 pneumonic and 1342 non-pneumonic X-ray images obtained from free of cost image database and 220 positive case profiles of the disease were obtained from open image database available at COVID-19 Radiography Dataset on Kaggle which includes radiology images of patients from a varied array of age groups.

Error Detection

Correlation is similarity between the two images or frames. Correlation function gives statistical correlation between random variables which exist between spatial temporal distance between two variables. Correlation value of error image and error free image are different. So correlation detects the error image. Correlation is used to determine 2D correlation coefficient between A and B matrices or vectors of the same size image m X n (Rajani & Khaparde, 2016a; Rajani & Khaparde, 2017; Rajani et al., 2017).

The normalized correlation function is,

$$Correlation, r = \frac{\sum_m \sum_n \left(A_{mn} - \bar{A}\right)\left(B_{mn} - \bar{B}\right)}{\sqrt{\sum_m \sum_n \left(A_{mn} - \bar{A}\right)^2 \sum_m \sum_n \left(B_{mn} - \bar{B}\right)^2}}$$

Where $r = 2D$ correlation coefficient between A and matrices or vectors of the same size image or frame $m\ X\ n$ and $\bar{A} =$ is the Mean of image matrix A & $\bar{B} =$is the Mean of B image matrix

The Correlation with threshold is found by trial and experimentations of different images and different type of errors.

Error Concealment

Error Concealment (EC) is hiding the errors at the decoder side (Rajani & Khaparde, 2016b). The digital image X-ray is analyzed initially for all the possible errors that might have occurred during the transmission of the X-ray image. Once the errors are detected using suitable algorithms, the raw image is passed on to the error concealment phase of the project that uses Frequency Selective Extrapolation algorithm. The rectified image then serves as the dataset for the ML algorithm which executes to determine whether the image is that of a Covid-19 patient or of a normal pneumonia affected patient. It is basically the process of reconstructing lost or deteriorated parts of the images. In EC algorithms such as Frequency Selective Extrapolation (FSE), X-ray image content of the appropriately received neighboring blocks is successively and collectively approximated by a weighted linear and simple combination of basis functions. This the misplaced or mislaid block is obtained by extrapolation in case of FSE error concealment. processing. Frequency Selective Extrapolation Algorithm (FSEA) is one of the best algorithm in Spatial

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Error Concealment algorithm (Rajani & Khaparde, 2016a; Rajani & Khaparde, 2017; Rajani et al., 2017). This mainly more useful for images with less number of errors. FSEA can conceal only block errors.

The error concealment algorithm works on the principle of spatial error concealment as shown below:

1. Discrete Linear Approximation
2. Principle of Successive Approximation
3. Selection of appropriate basis functions

DETECTION OF COVID-19

Data Pre-Processing and Data Augmentation

Data processing is used to perform operations on data to retrieve, transform, or change data through computer. It converts the raw data into clean data set. Correct pre-processing of the training data was done for removal of very less quality X-ray images (Rajaraman et al., 2020; Zhang et al., 2020). This will affect the accuracy of the trained and tested model. The X-ray scan was modified to zoom in by 20%, height shift (+10% or -10%), left and right shift (+10% or -10%) and rotation (+10% or -10%).

Data augmentation is increasing amount of data with help of information available from training data. After data augmentation, the training dataset with a total number of 485 training batches is obtained (Lei et al., 2020).

Loading a Pre-Trained Model, Training and Predicting

This model is used to identify COVID-19, Pneumonia and normal cases based on the images of Chest Xray. The identification is based upon categories of the data in the dataset, normal, pneumonia and pneumonia caused by COVID-19. For the examination of the proposed model, it is compared with the Resnet18 model on the COVID-19 dataset. Number of training batches are 485 and the Number of test batches are 18.

The Flow of detection of Covid-19 can be explained as follows:

1. Initially, all the required libraries necessary for the examination of the model are imported.
2. The dataset required for this research were obtained from image database available at
3. "COVID-19 Radiography Dataset" on Kaggle which includes radiology images of patients from a varied array of age groups. The next part is followed by the Image Transformation. The transformed image is needed because the Pytorch doesn't understand PIL images. That needs to be converted into tensor images.
4. Prepare the data pre-loader. In this part we have to create and train the chosen resnet18 model. It is pretrained from image network training dataset.
5. The detection of COVID-19 is done by examining the three important features of chest Xray.
   a. Peripheral distribution of POS.
   b. Ground Grass Opacity
   c. Vascular Thickening.

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Initially, there was a drastic fluctuation because the model was searching for important features as mentioned above that would make the result highly accurate. Once the features of the model have been found, the accuracy increases and it automatically decreases the validation loss. The time needed for training for each method is compared. The training time is measured based on the CPU time in microsecond.

OBJECTIVE QUALITY ANALYSIS

Objective quality analysis is done through following parameters are Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR) in dB, Structural Similarity Index (SSIM), Entropy and Time in seconds (Rajani & Khaparde, 2016a; Rajani & Khaparde, 2017; Rajani et al., 2017).

Mean Squared Error (MSE)

It measures the difference between original and distorted pixels. MSE is given by:

$$MSE\left(x,y\right)=\frac{1}{N}\sum_{i=1}^{N}\left(x_i-y_i\right)^2$$

where x_i and y_i should be of same class and N=total no. of pixels.

Peak Signal to Noise Ratio (PSNR)

The PSNR computes the peak signal-to-noise ratio, in decibels, between two images. The higher the PSNR, the better the quality of the compressed, or reconstructed image. The Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR) are the two-error metrics used to compare image or video reconstruction quality. It is the logarithmic representation of inverse of MSE. PSNR is given in decibels(dB) by:

$$PSNR\left(dB\right)=10log_{10}\left(\frac{\left(2^n-1\right)^2}{MSE}\right)$$

where n is number of colour /grey levels in image.

Structural Similarity Index (SSIM)

SSIM utilizes structural distortion as an estimate of perceived visual distortion. But most of the other approaches are error sensitivity-based methods. Based on the three computation terms, Luminance term, the Contrast term and the Structural term the Structural Similarity (SSIM) Index quality assessment index is calculated. The multiplicative combination of the three terms are used for overall index calculation. It is given by:

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$$SSIM(x,y) = \left[l(x,y)\right]^{\alpha} . \left[c(x,y)\right]^{\beta} . \left[s(x,y)\right]^{\gamma}$$

where

$$\text{luminance term}, l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu^2{}_x + \mu^2{}_y + C_1}$$

$$\text{contrast term}, c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x{}^2 + \sigma_y{}^2 + C_2}$$

$$\text{structural term}, s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3}$$

where μ_x, μ_y, σ_x, σ_y, and σ_{xy} are the local means, standard deviations, and cross-covariance for images *x, y*. If $\alpha = \beta = \gamma = 1$ (the default for Exponents) and $C_3 = \frac{C_2}{2}$ (default selection of C3)

Entropy

Entropy is a measure of image information content, which is interpreted as the average uncertainty of information source. In Image, Entropy is defined as corresponding states of intensity level which individual pixels can adapt. It is a statistical measure of randomness that can be used to characterize the texture of the input image.

$$Entropy, E = -\sum plog_2 p$$

where p contains the histogram counts.

Loss

It is the difference between the predicted value by the model and the true value. The most common loss function used in deep neural networks is **cross-entropy**.

$$Cross - Entropy = \sum_{i=1}^{n}\sum_{j=1}^{m} y_{i,j}\log(P_{i,j})$$

where, $y_{i,j}$ denotes the true value. It will be 1, if sample i belongs to class j and 0 otherwise and $p_{i,j}$ denotes the probability predicted by the model of sample i belonging to class j.

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Accuracy

It is one of the metrics used to measure the performance of the model.

$$Accuraccy = \frac{Number\ of\ Correct\ Predictions}{Total\ number\ of\ Predictions}$$

Most of the time, as the accuracy increases, loss will decrease.

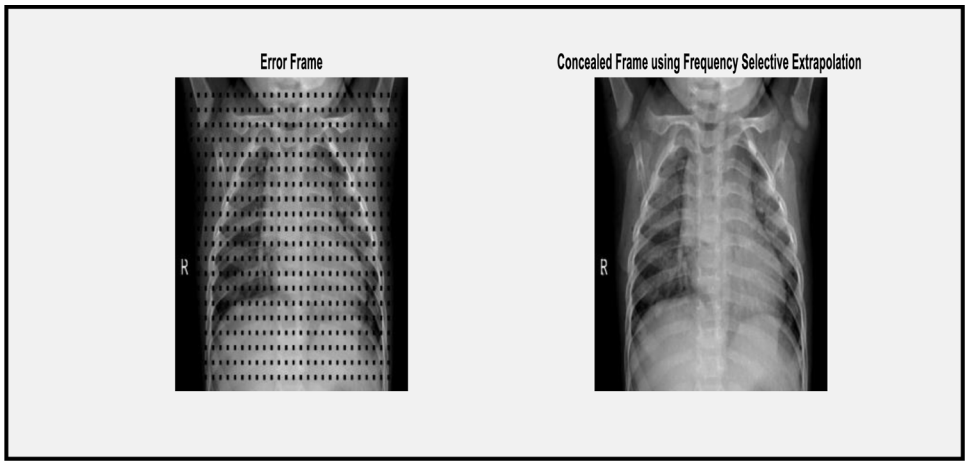
EXPERIMENTAL RESULTS

In the experiment results, first the error detection and concealment for Normal, Covid and pneumonia Patient's X-ray is discussed. Then detection of covid or not from the X-ray is analyzed.

Error Detection and Concealment

Following are the results of error concealment and image analysis performed on three medical images as in Figure 5, 6 and 7. The three following images are in the order of a normal patient's X-ray followed by a pneumonic and Covid-19 affected patient's X-ray. The Error Concealment using Frequency Selective Extrapolation algorithm performed on radiology images of normal patient is as shown in Figure 5.

Figure 5. Error Concealment of Normal Patient's X-ray



Extensive analysis is performed on these images and following conclusions are drawn. The analysis of the various image parameters has been done on 10 radiology samples. The table below shows the results of normal patient's radiology images. All the images used are in .jpg format.

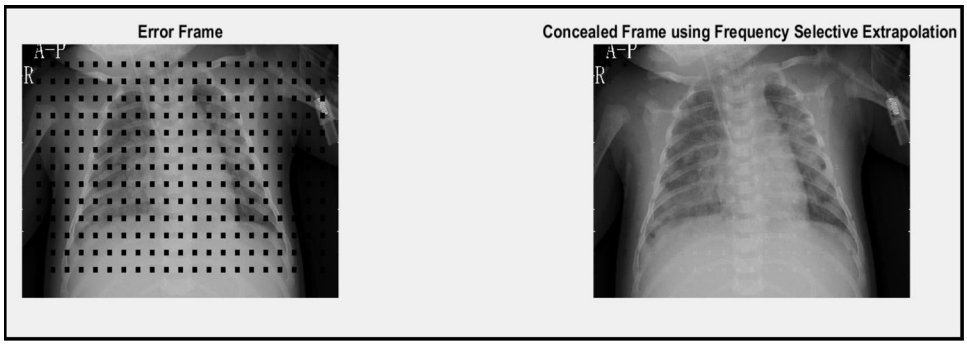
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Table 4. Image Analysis of normal patient's radiology images

		Erroneous Image				Error Concealed Image				
S. No.	Name of Image	MSE	Entropy	PSNR	SSIM	MSE	Entropy	PSNR	SSIM	Time taken
1	Normal X-ray 1	1351.5867	0.7642	6.7889	0.8111	10.8161	0.5877	27.7567	0.9182	5.52107
2	Normal X-ray 2	1898.9574	0.6899	5.4646	0.7931	10.27	0.4414	28.134	0.9152	8.5522
3	Normal X-ray 3	1643.8069	0.7838	29.0454	0.8076	8.1025	0.61	5.9731	0.921	8.3669
4	Normal X-ray 4	1866.7867	0.9673	5.2615	0.8399	5.7908	0.9343	30.3451	0.9173	3.9214
5	Normal X-ray 5	1789.6472	0.9138	6.5739	0.8564	9.1238	0.8451	27.6722	0.9232	8.7384
6	Normal X-ray 6	1866.7867	0.9673	5.2615	0.8399	5.7908	0.9343	30.3415	0.9173	3.7244
7	Normal X-ray 7	1876.8342	0.9453	5.1674	0.8346	8.5473	0.9209	28.4837	0.9138	3.2238
8	Normal X-ray 8	1790.5674	0.938	7.6354	0.8239	11.6473	0.8997	30.1903	0.9134	3.7802
9	Normal X-ray 9	1589.4539	0.9763	6.6845	0.8313	9.4759	0.9437	29.4836	0.9584	7.6445
10	Normal X-ray 10	1845.9283	0.9523	22.2382	0.8547	9.2334	0.9283	30.9291	0.9285	3.4822
	Average Values	1752.0355	0.8898	10.0121	0.8293	8.87979	0.8045	26.9309	0.9226	5.695507

The conclusions can be drawn from the table 4 is that, average MSE reduces from 1752.0355 to 8.8797(by 99.49%) and average Entropy reduced from 0.8898 to 0.8045 in concealed image than Error image. But average PSNR improves from 10.0121dB to 26.9309dB (by 62%) and average SSIM improves from 0.8293 to 0.9226 (by 11.25%) in concealed image. Thus, the concealed X-ray image is having good quality image which can be used for prediction of covid-19. The average time taken for concealing the error X-rays is 5.69 seconds.

Figure 6. Error Concealment of Pneumonia Patient's X-ray



The Error Concealment using Frequency Selective Extrapolation algorithm performed on radiology images of pneumonia patient is as shown in Figure 6. The table5 shows the results of pneumonia patient's radiology images. 10 pneumonia patient's X-ray images in .jpeg format is used for analysis.

The conclusions can be drawn from the table 5 is that, average MSE reduces from 1866.1408 to 6.5058 (by 99.65%) and average Entropy reduced from 0.6083 to 0.27119 in concealed image than Error image. But average PSNR improves from 5.76061dB to 30.5216 dB (by 81%) and average SSIM improves from 0.8293 to 0.9226 (by 12%) in concealed image. Thus, the concealed X-ray image is having good quality image which can be used for prediction of covid-19. The average time taken for concealing the error X-rays is 3.68 seconds.

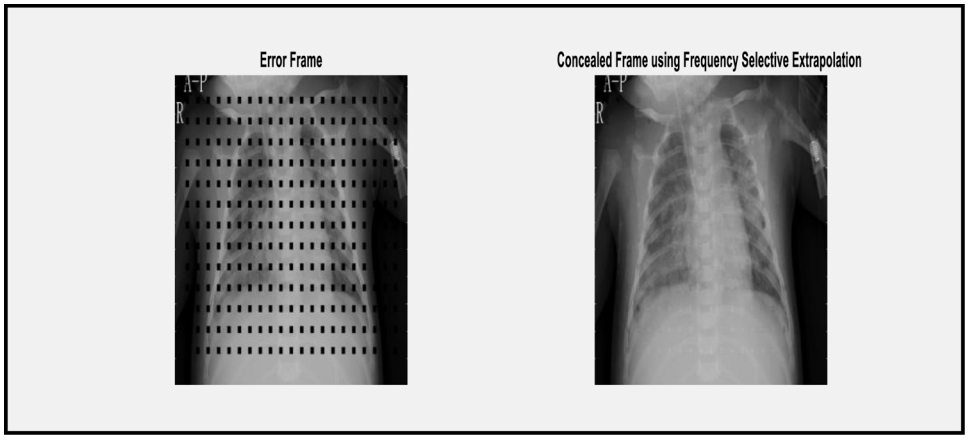
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Table 5. Image Analysis of Pneumonia Patient's Radiology Images

		Erroneous Image				Error Concealed Image				
S. No.	Name of Image	MSE	Entropy	PSNR	SSIM	MSE	Entropy	PSNR	SSIM	Time taken
1	Pneumonia X-ray 1	1192.0302	0.5126	6.8952	0.8031	5.7162	0.1816	30.177	0.9164	2.519
2	Pneumonia X-ray 2	2298.0052	0.5438	4.2206	0.7882	6.231	0.2165	28.8885	0.9073	3.6643
3	Pneumonia X-ray 3	1833.4626	0.5581	5.1084	0.7986	6.6393	0.2429	29.5199	0.9179	2.595
4	Pneumonia X-ray 4	1845.5748	0.6474	6.4894	0.7322	7.2161	0.1652	39.7269	0.9271	4.388
5	Pneumonia X-ray 5	1839.3737	0.5289	5.3911	0.7362	6.2636	0.2291	30.1871	0.9354	3.4922
6	Pneumonia X-ray 6	2267.3732	0.6452	5.3782	0.8217	6.2711	0.1902	29.2719	0.8992	3.2821
7	Pneumonia X-ray 7	1842.5432	0.7822	6.3812	0.8901	6.1527	0.3812	27.281	0.9181	4.2818
8	Pneumonia X-ray 8	1829.2871	0.6382	6.2681	0.8279	8.1678	0.1828	29.7392	0.9364	3.9281
9	Pneumonia X-ray 9	1834.782	0.5884	6.2002	0.832	5.8298	0.3427	30.7491	0.9273	5.3981
10	Pneumonia X-ray 10	1878.9763	0.6387	5.2737	0.8541	6.5711	0.5797	29.6762	0.9132	3.2801
	Average Values	1866.1408	0.60835	5.76061	0.80841	6.50587	0.27119	30.52168	0.91983	3.68287

The Error Concealment has been performed on radiology images of covid patient is as shown in Figure 7. The table6 shows the results of covid patient's radiology images. 10 pneumonia patient's X-ray images in .jpeg format is used for analysis.

Figure 7. Error Concealment of Covid-19 Patient's X-ray



The conclusions can be drawn from the table 6 is that, average MSE reduces from 2085.0584 to 7.0614 (by 99.66%) and average Entropy reduced from 0.6944 to 0.5441 in concealed image than Error image. But average PSNR improves from 5.9312dB to 29.1024 dB (by 76.61%) and average SSIM improves from 0.8201 to 0.8508 (by 3.6%) in concealed image. Thus, the concealed X-ray image is having good quality image which can be used for prediction of covid-19. The average time taken for concealing the error X-rays is 3.76 seconds.

Results of Detection of Covid-19. The characteristic symptoms of Covid-19 are shown in a tabular manner: The Machine Learning algorithm is trained using supervised learning algorithm to identify the main symptoms of Covid-19 and declare the results accordingly.The basic idea behind the entire procedure is that the image that arrives from a remote location or from a variety of radiology facilities

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Table 6. Image analysis on Covid Patient's Radiology Images

		Erroneous Image				Error Concealed Image				
S. No.	Name of Image	MSE	Entropy	PSNR	SSIM	MSE	Entropy	PSNR	SSIM	Time taken
1	Covid X-ray 1	2519.2493	0.4553	3.9034	0.795	13.3816	0.0088	26.6511	0.9067	2.6504
2	Covid X-ray 2	1866.7867	0.9673	5.2615	0.8399	5.7908	0.9343	30.3451	0.9173	4.1955
3	Covid X-ray 3	1868.7869	0.6894	5.2075	0.8186	6.6789	0.8364	27.9675	0.9185	3.6310
4	Covid X-ray 4	1845.6238	0.6382	5.2379	0.8191	6.1827	0.5283	28.6181	0.9162	3.7193
5	Covid X-ray 5	1894.7172	0.7282	5.2387	0.8253	6.6282	0.6282	28.6722	0.9722	4.2871
6	Covid X-ray 6	2531.7191	0.8324	6.3232	0.8201	5.2973	0.5664	30.2373	0.9627	3.1797
7	Covid X-ray 7	1892.3256	0.4202	5.1879	0.8211	5.1333	0.3021	29.2718	0.8933	3.6672
8	Covid X-ray 8	2782.7989	0.6891	7.2912	0.8273	7.8791	0.5829	29.8739	0.9122	4.1801
9	Covid X-ray 9	1833.8282	0.7283	7.3872	0.8223	5.2839	0.3929	31.7391	0.1891	3.2828
10	Covid X-ray 10	1814.7478	0.7951	8.2738	0.8127	8.3582	0.6611	27.6483	0.9196	4.8179
	Average Values	2085.0584	0.6944	5.93123	0.8201	7.0614	0.5441	29.1024	0.8508	3.7611

is prone to a lot of errors either because of poor transmission or the quality of image is not deemed to be fit as per the required criteria. The error concealment algorithm bridges the gap between the requirements. After a detailed analysis wherein the image quality is considerably increased, the image is given to the supervised learning algorithm. The supervised algorithm then gives a detailed predictive analysis which is the expected performance of this model.

The closer the image is to its ideal parameters; the more effective prediction can be expected out of the proposed model. The image quality should not be a hindrance to the algorithm, so that a more reliable prediction is made. As a matter of fact, various error concealment procedures can be performed, but Frequency Selective Extrapolation algorithm suits the requirements of the model.

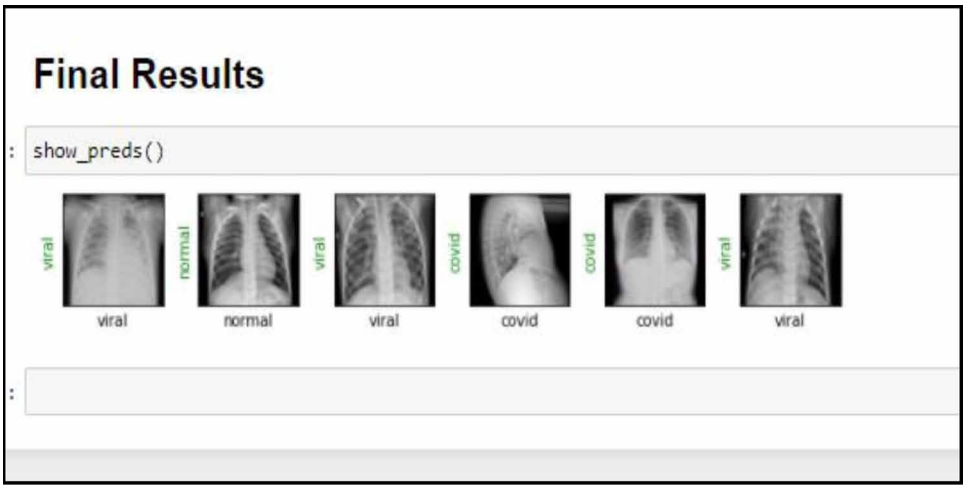
The image analysis parameters as observed for various X-ray samples are shown in above table. Normal, Pneumonia and Covid X-ray error images are concealed. The lesser the value of MSE (Mean Squared Error), the better is the quality of X-ray. As can be seen from the table, value of MSE has been considerably reduced in the error concealed image. This ratio is used for the measurement of quality between the original and a compressed (manipulated) image. Higher the PSNR, the better the quality of the compressed, or reconstructed image. As is obvious from the table, Peak Signal to Noise Ratio (PSNR) has been increased in the error concealed image. The Structural Similarity Index (SSIM) is a metric that determines image quality. The SSIM values ranges between 0 to 1. The MSE of Error concealed image is lesser, where as PSNR and SSIM is improved which indicates that a better-quality X-ray image is reconstructed using Error Concealment.

B. Detection of Covid-19

X-ray can be taken from anywhere and send it through any communication medium. Even if error is added, it can be removed using Error concealment algorithms. Automated AI based system will be used for prediction of Normal, COVID-19 and Pneumonic cases from each X-ray images. Besides, it makes detection of COVID-19 infection, it is less costly and portable. This device can be stored in less stringent conditions, making it more effective.

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Figure 8. Detection as Viral pneumonia, Normal & Covid-19



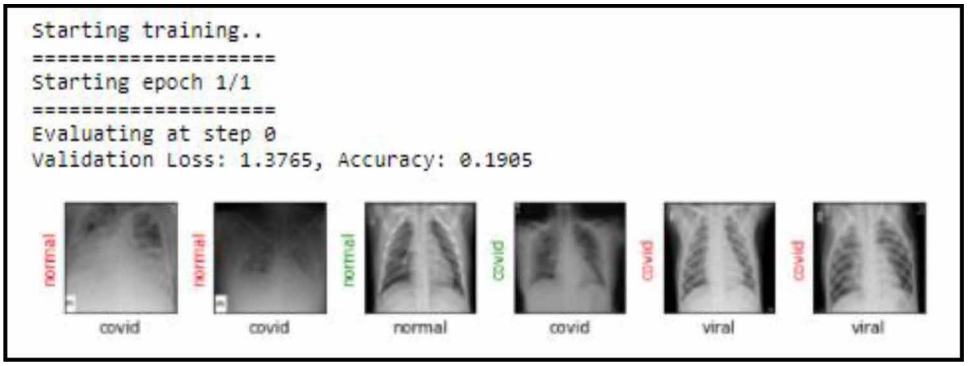
The proposed research work use ResNet-18 model and train it on a COVID-19 Radiography dataset. 3000 Chest X-Ray images are present in the dataset which is used for classifying the scan into Normal, Viral Pneumonia and COVID-19. The Convolutional Neural Network (CNN) used here for the prediction of classes. Figure 8 shows the detection of radiography image as Normal, Viral or Covid-19.

Here each evaluating step includes a batch size of 6 is taken for result and analysis. The validation loss is calculated in each case and analysis is done accordingly as follows:

If validation loss >> training loss, it is known as overfitting.
If validation loss > training loss, it is known as some overfitting.
If validation loss < training loss, it is known as some underfitting.
If validation loss << training loss, it is known as underfitting.

Also, accuracy in each case is calculated. The stopping condition for evaluation is kept as accuracy greater than 95%.

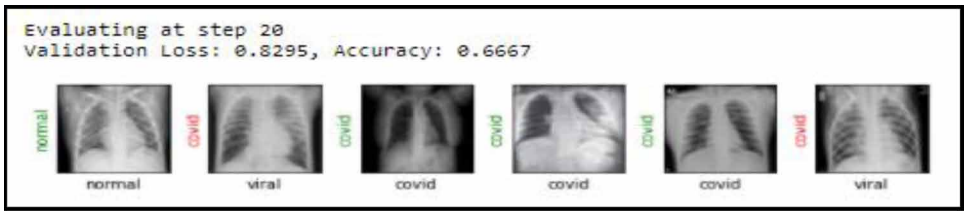
Figure 9. Staring Evaluating Step at 0



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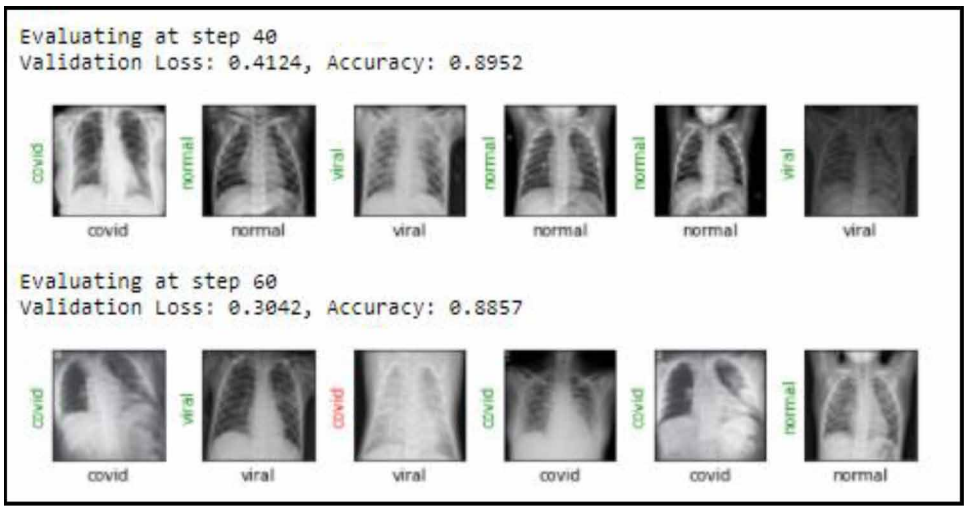
1] After initializing the training, step 0 is evaluated. In this step, Correct outcomes are 2 and Incorrect outcomes are 4. Thus, the validation loss is obtained as 1.3765 and accuracy is 19.05%.

Figure 10. Evaluating Step at 20



2] The next evaluating step is taken as step 20. In this step, the correct outcome is received as 4 and Incorrect outcomes as 2. The validation loss is obtained as 0.8295 and accuracy is 66.67%.

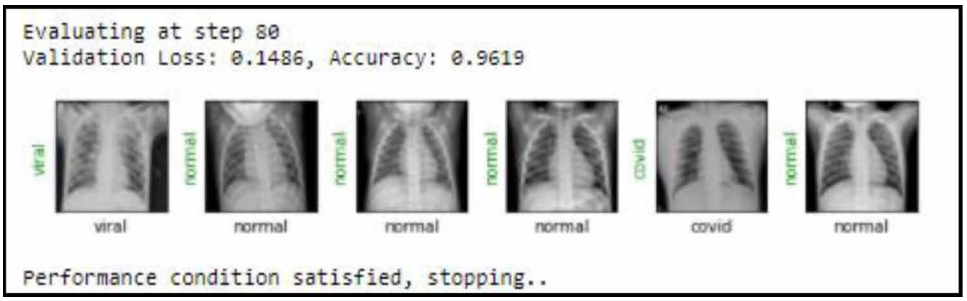
Figure 11. Evaluating Step at 40 & 60



3] The Subsequent steps includes evaluation at step 40 and 60, where the accuracy is gradually increasing. In evaluating step 40, the validation loss is found to be 0.4124 and accuracy is 89.52%, whereas, in evaluating step 60, the validation loss is found to be 0.3042 and accuracy is 88.57%.

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Figure 12. Evaluating Step at 80



4] In evaluating at step 80, the validation loss is found to be 0.1486 and accuracy is 96.19%. The condition for accuracy is given as more than 95%. This condition is successfully satisfied, so no need of further evaluation is done.

Once the stopping condition is achieved, the covid prediction analysis can be summarized as in Table 7. The conclusion that can draw from this table7, is as follows is that accuracy is increasing as the number of evaluating steps increase. With the increase in accuracy, the probability of receiving the correctly detected outputs is also increased. Validation loss also decreases. The condition for accuracy in this case is given as above 95% for a batch size of 2. This achieved here along with all outcomes correct.

Table 7. Covid Prediction Analysis Table

Sr. No.	Evaluating Step	Validation Loss	Accuracy (%)	Batch Size	Correct Outcomes	Incorrect Outcomes
1	0	1.3765	19.05	6	2	4
2	20	0.8295	66.67	6	4	2
3	40	0.4124	89.52	6	6	0
4	60	0.3042	88.57	6	5	1
5	80	0.1486	96.19	6	6	0

CONCLUSION

The research work done for concealment and detectection of COVID-19. This autonomous device is used for the prediction of normal, pneumonia or COVID-19 from the given X-ray image. The corona virus spreads at exponential rate, there is a huge shortage of medical testing kits all over the world, especially in rural area. The people can take chest X-rays from anywhere and transmit it for diagnosis through any transmission medium. Most of the transmission medium can add error or loss of data. So, the error detection and concealment of the error can be done through this device. The most affected part of the human body by the virus is the respiratory system. There is a need of low cost, portable device with fast and accurate detection capabilities of the novel corona virus from X-ray, independent of pathology. Upon successful development of this biomedical device, it can be used at rural-urban healthcare system

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to analyze the radiological and pathological data. This device provides the enhanced support to Radiologist and clinical experts for fast and accurate COVID-19 detection.

The key advantage of the proposed research is that it will substantially decrease the overhead and expenditure upon the government when it comes to mass testing of the cases. This form of testing would also be a convenient experience to the patients and a second opinion to doctors. The drawback of the proposed model is the feasibility of production of radiology images in remote locations or economically backward locations. The transmission of reliable images through a medium might also be difficult to realize the entire procedure. But taking into account the benefits of hands-free testing and a promising error-free prediction, this model could be expected to reap revolutionary outcomes if realized with proper protocols.

FUTURE SCOPE

The Laboratory level testing and calibration of this device will be done at institute in consultation with the clinician and hospital partners. The device will be thoroughly tested and validated at hospital/society level in consultation with hospital partners and experts, social activists and NGOs. The test results acquired from this Biomedical device will be verified by the clinical experts. There is a possibility of existence of suitable parameters for the discussed model which can help to classify and arrange the radiology images with greater precision. Further optimization of RESNET-18 may be possible as a future prospect.

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Chapter 9
COVID-19 Data Forecasting and Spread Visualization Using ML

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ABSTRACT

The COVID-19 global pandemic has affected everyone's day-to-day life. The COVID spread data is increasing rapidly which needs to be visualized in some format. The statistical data includes infected, recovered, and the death count which is visualized by various tools. This project presents an interactive dynamic dashboard to display the details about the COVID-19 patient reports, scheduled reports, timely reports, geographical reports including state-wise, district wise. It should have options to display the metrics using charts, graphs, etc. Application features include registration, download report in multiple formats, email the report, schedule a report, share a report. Users can check for Epass availability; the decision will be taken by checking the covid-affected counts on the source and destination. Patient details will be stored in the cloud. The model includes a prediction of upcoming covid-affected count using ML.

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INTRODUCTION

Coronavirus disease (Coronavirus) achieves the 2019-2020 overall pandemic. This issue has been achieved through the Serious Intense Respiratory Disorder Covid. Pretty much every nation has been influenced by the staggering Coronavirus sickness (COVID-19). The world is going through an incredible vulnerability. Without a doubt, the Coronavirus has put the world economy at a significant danger. The Indian economy has been hit hard by the continuous Coronavirus pandemic-driven worldwide emergency. The whole world is going through extraordinary vulnerability. There are, fundamentally, two significant difficulties that the Indian economy is looking at this point. First is to save the country from the spread of Coronavirus (COVID-19), which is a wellbeing crisis. Saving lives is the main, the chief worry of the public authority. Second is to save the economy from the unfurling financial vulnerability because of the double impacts of the Coronavirus pandemic and the worldwide and public lockdown. World Wellbeing Association suggested three lakhs cases and around two lakhs passings, In this part, we have arranged and developed an intelligent unique dashboard that offers confirmed data about Coronavirus. Also, in see on this information, we have arranged an AI model to imagine and estimate the improvement of cases and passings worldwide and through country.

The COVID spread information is expanding quickly which should be imagined in some configuration. The factual information incorporates contaminated, recuperated, and the passing check which is imagined by different devices. In light of constant information it is imperative to break down it for settling on choices to handle the expanding tally of cases and passings. This exploration work incorporates the graphical portrayal of COVID cases and a model which predicts the future spread check. Booked reports,Timely reports, Geographical reports incorporate State-wise, District insightful. having alternatives to show the measurements utilizing diagrams,charts, and so forth.

In this model the information will be gotten from the POST API. Model incorporates Application Features like enrollment of the patient,download the reports in numerous arrangements, for example, pdf, dominate, picture, and so forth. Clients can share the Coronavirus tally reports by means of email and timetable a report as per time. Clients can likewise check for E-pass accessibility,the choice will be taken by checking the COVID influenced depends on the source and objective. This model will assist individuals with examining and envision the information tally.

Machine mastering (ML) is one of the most advanced standards of artificial talent (AI) and offers a strategic method to developing automated, complicated, and goal algorithmic techniques for multimodal and dimensional biomedical or mathematical statistics analysis (2021). The ML algorithms can check and modify its shape based on a set of determined data with adaptation achieved by means of optimizing over a price feature or an objective and has already proven possible for diagnosing, detecting, containing, and therapeutic motoring of many diseases(2021).

ML strategies can be categorized in four ways: Supervised mastering techniques are ML learning methods or algorithms that bind previous and modern-day datasets with the help of labeled statistics to predict future occasions and the learning process starts off evolved with a dataset training process and develops a focused undertaking to predict output values (2021). Unsupervised gaining knowledge of is ML strategies that are used when the training dataset is non-classified or non-labeled. The getting-to-know techniques deduce a function to extract hidden knowledge or a sample from the unlabeled dataset. The approach does not become aware of the suitable output however as an alternative extracts remark from the dataset to discover hidden patterns from the unlabeled dataset. Semi-supervised learning techniques are mastering techniques that lie between supervised mastering strategies and unsupervised gaining

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knowledge of techniques, where, where labeled and non-labeled datasets are used in the coaching procedure. Generally, the studying strategies reflect on consideration on a smaller labeled dataset and a large unlabeled dataset. Reinforcement gaining knowledge for strategies have interaction with the studying surroundings with the aid of actions to detect mistakes. Delayed rewards and trial and error searches are some of the frequent aspects of the reinforcement mastering techniques and the techniques are used to perceive the best behavior in a particular context to make bigger the performance of the mannequin.

The PC acquiring data on the framework begins with accumulating data independently that is, from a spread of resources. Then after the next stage is to repair the pre-handled statistics to repair information related problems and breaking factor sector dimension via erasing invalid record statistics to select out fascinating realities. However, Sometimes, the cost of the dataset can be very for the framework to shape a decision, in this way, PC acquiring information on calculations are planned utilizing others questioning like measurements, thinking the board, and opportunity, and so on. to look into data and extricating gainful and novel settlement or concealed examples or data from past encounters. the ensuing step is that the prevalent exhibition differentiation of the fashions and inner the stop, is model enhancement improving the mannequin through the use of late datasets and guidelines. Machine learning techniques are getting utilized in an extraordinarily scope of territories like remedy, designing, practise, assembling and introduction, gauge, web site company company, and robot amongst others.

BACKGROUND

According to particular papers available in writing, there are a couple of studies that emphasize pattern investigation on covid data. So to communicate with the audience data visualisation technique will be the best for the front and centre users which works in the area of the Healthcare and to the public. This will work to understand the various characteristics of the covid-19 and the current situation. First covid interactive dashboard was developed by the Johns Hopkins University which attract information of the data and display the count of the cases along with this charts and all the bubble graph, histograms also shown on the site. With the previous work done in the field of the covid data dashboard pictures showing the count of the cured people and death count country wise but no research was done on the sharing of this data with different formats. In this chapter interactive and dynamic dashboard was developed with the updated data of the active patient, recovered and death count. which will be displayed in the format of the graphs and charts can be shared with one or more uses via different modes. This will offer the concise way to express the pandemic situation. Along with this the timely data will be mapped and on dashboard. The investigations on the Indian covid data patterns and count could be shown in some graphical format. The as of now reachable review for the Coronavirus comprises of current count and deaths. In this chapter covid outbreak prediction has done using SVM machine learning algorithm.

According to research Containment measures are intended to avoid an outbreak trajectory in which a large number of people get sick at the same time (Mustafa, 2020). This is what the visualization shows and this is the reason that limiting the magnitude of peak incidence of an outbreak is important (Mustafa, 2020). Health systems can care for more patients across an outbreak when the number of cases is spread out over a long period rather than condensed in a very short period (Research and Statistics: Coronavirus Disease (COVID-19), 2020). This research separates the survey of other papers and journals in different areas like history of covid, Research and Statistics, ML in field of prediction, techniques for data visualization, big data in data forecasting.

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1. How ML can Help with COVID-19 Outbreak?

Much research has already been carried out on the usage of a variety of machine learning techniques for diagnosing and predicting covid-19 contamination and recovery. In the work of information mining, predictive models for covid-19 patients healing have been developed with four information mining algorithms however amongst them, the model made of the selection tree has the easiest accuracy of 99. 86%. Machine learning (ML) is one of the most advanced concepts of artificial intelligence (AI), and provides a strategic approach to developing automated, complex and objective algorithmic techniques for multimodal and dimensional biomedical or mathematical data analysis (Raphael D, 2020). ML has already shown potential for diagnosing, detecting, containing, and therapeutic motoring of many diseases (Haruna AA, 2019).Lot of research has been done in prediction of covid-19 disease and outbreak forecasting, In the work of (Muhammad LJ, 2018) data mining predictive model for COVID-19 patients recovery were developed with four data mining algorithms but however among them, model made of the decision tree has the highest accuracy of 99.85%. In this work, decision tree, logistic regression and naive, SVM and ANN supervised learning classification models for prediction of COVID-19 infection using an epidemiology dataset for positive and negative COVID-19 cases in Mexico were developed. The performance of all models was evaluated based on accuracy parameters (Muhammad, Supervised Machine Learning Models for Prediction of COVID-19 Infection using Epidemiology Dataset, 2021). (Ardabili SF, 2020)

In the journal article written by (Ardabili SF, 2020) provides an initial benchmarking to demonstrate the potential of machine learning for future research. This paper further suggests that a genuine novelty in outbreak prediction can be realized by integrating machine learning and SEIR models (Ardabili SF, 2020). The covid pandemic has become national threat at global level so it is very important to search for outbreak prediction technique to overcome this situation.

In the work of convolutional neural networks that predict novel coronavirus with x-ray images have been developed. The deep mastering technique, which is one of the sub-branches of ML, inspired by the structure of the human brain is used for the computerized prediction of covid-19 to patients. A dataset with chest x-ray photographs has been used, and pre-trained fashions together with InceptionV3, ResNet50, and Inception ResNetV2 were skilled and examined on the dataset. The performance result of the find out showed that the ResNet pre-trained mannequin gave the perfect accuracy among the three models with good outcome. Therefore, this suggests that the mannequin can help health workers to make choices in clinical practice with high-performance accuracy, which can also notice covid-19 to in the early degrees of infection. In the work of a modified susceptible-exposed-infectious-removed (SEIR) Model and ML Model for prediction of the style of the covid-19 pandemic in China have been developed below public fitness interventions. The models have been effective in predicting the pandemic peaks and sizes. Population migration information earlier than and after updated covid-19 epidemiological information had been integrated into the SEIR Model to derive the pandemic curve. The ML strategy used to be skilled on 2003 SARS records to predict the pandemic. In the work of statistics mining and deep studying, the pilot learns about were carried out to predict covid-19 incidence via levering Google vogue data in Iran. Long Short-Term Memory and Linear Regression Models have been used to estimate the number of covid-19superb cases. The models were evaluated with root suggest rectangular error (RMSE) metric and 10 folds cross-validation techniques, respectively. Such predictions can support healthcare managers and coverage makers with planning, allocating, and deploying healthcare assets effectively. Reference recognized an intrinsic covid-19genomic signature with the use of an ML-based

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alignment-free approach. The predicted vaccine in the find out about presents new strategies for fantastic and protected covid-19vaccine development. Reference presented a data-driven ML approach for the evaluation of the covid-19pandemic from its early contamination dynamics especially inflation counter over time, the usage of US information beginning from the first case on 20th January 2020. The actionable public fitness insight used to be extracted which consists of infectious force, price of the slight infection turning into serious, estimates for asymptomatic infections, and prediction of new infections over time.

The related works which have been reviewed so ways imply that ML techniques and different artificial mind techniques have completed essential roles in prediction, diagnosis, and containment of the COVID-19 pandemic, which could assist in restricting the huge burden on confined healthcare systems. To the great of our knowledge, no paintings have been stated so ways using epidemiology categorized datasets for great and horrible COVID-19 instances in Mexico for development of supervised ML models for prediction of the COVID-19 contamination. Therefore, the prevailing observe intends to test out those gaps. Much research has already been finished with the usage of quite a few artificial expertise for diagnosing and predicting COVID-19 infection and recovery. In the paintings of statistics mining predictive model for COVID-19 patients restoration had been advanced with 4 statistics mining algorithms however alternatively among them, the model manufactured from the selection tree has a pleasant accuracy of 99.8%. In the paintings of convolutional neural networks that are expecting novel coronavirus with x-ray snapshots had been advanced. The deep learning technique, that is one of the sub-branches of ML, stimulated via way of means of the usage of the form of the human intelligence is used for the automated prediction of covid to sufferers. A dataset with chest x-ray snapshots become used, and pre-skilled models which consist of InceptionV3, ResNet50, and Inception ResNetV2 were knowledgeable and tested on the dataset. The overall performance gives up the result of the study showed that the ResNet pre-skilled version gave an appropriate accuracy among the 3 fashions: 98%. As more individuals found out about the infection and got the message to socially remove, they either disregarded or noticed wellbeing admonitions, incompletely or totally. Singular decisions relied upon an assortment of variables: age, cultural qualities (yielding to power or libertarianism) and monetary need to work, among others. This, thus, prompted a cry to open the economy. While financial action should be rebooted, the way in which we do it is probably going to assume an enormous part in the all out number of passings coming about because of this pandemic. This likewise expanded joblessness to record levels in the US and different countries — to numbers unheard of since the 1929 Great Depression. Coronavirus disease, hospitalization and passing bends were enhanced by the media altogether influenced nations as residents were asked to "cover at home" and "smooth the bend." because of social changes, two arrangements of information likewise changed Case information, Joblessness information. Mediations, for example, shutting organizations and schools shut down monetary action and brought about a gigantic decrease in the interest for countless products and ventures. Furthermore, new cases and hospitalizations began dropping in various nations and US states, which had the planned impact of lessening passings – yet additionally, unreasonably, caused the first projections to appear to be ridiculously skeptical (wrong), accordingly opening up the model designers to analysis.

2. What Research has been done yet for This and why Statistics Play an Important Role in COVID?

The total number of cases is what important for research related to pandemic which is unknown. To understand the scale of the COVID-19 outbreak, and respond appropriately, we would want to know how

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many people are infected by COVID-19 and want to know the total number of cases (Mustafa, 2020). However, the total number of COVID-19 cases is not known. It is unknown by us at Our World in Data, or any other research, governmental or reporting institution (2020).While the researchers are trying to detect the cases based on data provided by government but this can be made simple with the help of data visualization to understand pattern. Many countries hide their count at global scale but this will create issue in model making as it will be less statistical. COVID-19 leads to a number of symptoms, but from what is known currently some symptoms are much more common than others and for this reason we need to look at the available data (Mustafa, 2020). Introduction Early reports of COVID-19 cases and deaths may not accurately convey community-level concern about the pandemic during early stages, particularly in the United States where testing capacity was initially limited. Social media interaction may elucidate public reaction and communication dynamics about COVID-19 in this critical period, during which communities may have formulated initial conceptions about the perceived severity of the pandemic Methods Tweets were collected from the Twitter public API stream filtered for keywords related to COVID-19 (Cuomo, 2021).This will take a lot of time to do research and then find the data. Here API will help to provide up to date data count for prediction.

WHO has effectively speed up the Research and development to accelerate immunizations, diagnostics, and therapeutics. These examinations use time-arrangement data from the John Hopkins College information base and present anticipating the utilization of the ARIMA model, Dramatic Smoothing strategies, SEIR life-sized model, and Relapse Model. We continued documenting the information as there was simply need of recorded examination of information. It changes quick and comes in assortments of structures that are hard to oversee and handle utilizing RDBMS or other conventional advancements.

The worker side augmentations are only the advancements that are utilized to make dynamic Web pages. As a matter of fact, to give the office of dynamic Web pages, Web pages need a compartment or Web worker. To meet this necessity, free Web worker suppliers offer some exclusive arrangements as APIs (Application Programming Interface). These APIs permit us to assemble programs that can run with a Web worker. For this situation, Java Servlet is additionally one of the segment APIs of Java Platform Enterprise Edition which sets principles for making dynamic Web applications in Java.

Prior to finding out about something, it's imperative to know the requirement for that something, dislike that this is the lone innovation accessible for making dynamic Web pages. The Servlet innovation is like other Web worker expansions like Common Gateway Interface (CGI) contents and Hypertext Preprocessor (PHP). Notwithstanding, Java Servlets are more satisfactory since they address the constraints of CGI, for example, low execution and low degree versatility.

Thus, this recommends that the model could help strong individuals make choices in clinical exercise with ordinarily outrageous exactness and execution, which could besides be considered in 2019 nearby the early degrees of tainting. Wiped out delicate uncovered overwhelming variable model sheets (SEIR) and ML model were made to predict. Generally talking, the motivation behind this revelation is to foresee the destiny of COVID-19 with an emphasis on the wide scope of ongoing noticed cases, the variety of passings, and the affected style of recuperation. In SVM, support vectors are the datapoints which are nearest to the hyperplane is called support vectors. Isolating line will be characterized with the assistance of these information focuses. Hyperplane is a choice plane or space which is split between a bunch of items having various classes. Margin might be characterized as the hole between two lines on the wardrobe information points of various classes. It very well may be determined as the opposite separation from the line to the help vectors. Huge edge is considered as a decent edge and little edge is considered as a terrible margin. The principle objective of SVM is to separate the datasets into classes

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to track down a most extreme negligible hyperplane and it very well may be done in the accompanying two stages, to start with, SVM will produce hyperplanes iteratively that isolates the classes in most ideal manner. At that point, it will pick the hyperplane that isolates the classes accurately.

3. How Data Visualization will Help to Understand the Current Situation?

Prior studies identified visualization related benefits and some methods which can be used for visualization. This article give a glimpse of how data visualization can help in the understanding of COVID-19 (Joao L. D. Comba, 2020). It shows different types of models showing the visualization. The example in this shows how multidimensional projections and network visualizations can help the literature exploration of papers that describe novel coronavirus research and as new research about COVID-19 is published, there is a great need to review up-to-date literature and treatments conveniently (Joao L. D. Comba, 2020). In (C. Leung, 2020) journal paper author described how big data tools have helped in visualizing covid data to get better understanding. Knowledge discovered from these epidemiological data helps researchers, epidemiologists and policy makers to get a better understanding of the disease, which may inspire them to come up ways to detect, control and combat the disease. As "a picture is worth a thousand words", having methods to visualize and visually analyze these big data makes it easily to comprehend the data and the discovered knowledge (Big Data Visualization and Visual Analytics of COVID-19 Data, 2020). According to the studies if we have a better visualisation techniques and tools we can predict data and check for a pattern for the next outbreak so it will help to overcome this pandemic situation by arranging some help in advance so that we can face the next outbreak properly with adequate healthcare management. Research which has been done in the above paper had used the data from the Twitter and other social media handlers,But this will take time and machine power to check the feed and then generated data according to it. So in this research paper we have taken the data from different official sites which is already in JSON format so it will take less time to process and visualise than above studies.

The following table includes some paper surveys regarding ML models used for predictions:

ISSUES, CONTROVERSIES, PROBLEMS

Problems Occurred During Data Gathering

The initial troubles for the large variety of model predictions may be associated with the shortage of statistics. Till the middle of February, there were once too few records of showed instances. This changed into an essential situation and the reliability of records was once extra trouble. However, strong version estimations that embody most opportunity Bayesian interference strategies think about the uncertainty of the information reasserts via way of means of manner of permitting the information at each thing to comply with a probabilistic distribution. This means that the shortage of statistics has been a greater severe concern.

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Table 1.

Sr No	Paper name	Author name	Methodologies	Disadvantage
1	Supervised Machine Learning Models for Prediction of COVID-19 Infection using Epidemiology Dataset	L. J. Muhammad, Ebrahem A. Algehyne, Sani Sharif Usman	Supervised ML models for COVID-19 infection were developed during this work with a choice tree, logistic regression and naive Bayes learning algorithms using an epidemiology labeled dataset of positive and negative COVID-19 cases.	The model developed with decision tree happened to be the simplest model among all models developed in terms of accuracy with 94.99% in comparison with other models developed with logistic regression, naive Bayes, SVM and ANN which have 94.41%, 94.36%, 92.40% and 89.20% accuracy respectively.
2	Machine learning models for covid-19 future forecasting	Ramesh Kumar Mojjada,, Arvind Yadav	The study findings show that in sight of the existence and dimension of the dataset, ES performs better within the current forecast domain.	LR and LASSO have both been effective in estimating and verifying the death rate to a point. The effect of ups and downs of the info collection is badly achieved by SVM altogether the cases.
3	A machine learning forecasting model for COVID-19 pandemic in India	R.Sujath,Jyotir Moy Chatterjee	The multilayer perceptron method is giving good prediction results than that of the.Linear regression and Vector auto regression method using WEKA and Orange.	The size of knowledge available is large and gathering information and getting a stimulating pattern out of the cumulated data may be a challenging task.
4	Predicting the growth and trend of COVID-19 pandemic using machine learning and cloud computing☆	Shreshth Tuli,Shikhar Tuli	Using the proposed Robust Weibull model supported iterative weighting, we show that our model is in a position to form statistically better predictions than the baseline.	The baseline Gaussian model shows an exaggerate picture of the COVID-19 scenario.

False Counts

The key trouble that explains the range of the version predictions is appreciation of how examined instances evaluate with the version forecasts. Some time officials hide the number of cases at country level which causes issue while testing the model. Confirmed instances are humans who're infected and feature made touch with the health facility and whose contamination has been tested positive. In contrast, the 'inflamed compartment' withinside the transmission models include people who've proven symptoms and symptoms and signs and symptoms and were tested and additionally folks that can also additionally moreover or can also additionally moreover now no longer have symptoms and symptoms and signs and symptoms and feature now no longer been examined. The ratio of the cumulative proven instances to the cumulative infected humans is the case-contamination ratio. But, why is that this trouble for modeling the covid-19 transmission in India? In model calibration for estimating transmission rate, it's far important to reduce fee the whole range of infectious people with the resource of the case-contamination-ratio to decide the duplicate huge variety (R0), the dimensions of the epidemic, as nicely because the peak time. Thus, if attempting out isn't done at a great favored degree, the model predictions are misspecified. Increasing sorting out for covid-19 is, therefore, critical.

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There are extraordinary concerns. These relate to the models used and the manner they may be envisioned. Given showed-case records, there's a linkage between the version parameters and the transmission rate. Different combinations of those parameters can yield wonderful model predictions. This is referred to as the non-identifiability of the version. The manner wherein this trouble is addressed extensively affects the reliability and the predictability of the fashions. Standard non-linear models fail to deal with this trouble. The extraordinary trouble that extensively affects the version predictions is the choice of the model itself. The choice of a suitable version to explain the epidemic is critical. In a complex version, diverse organic and epidemiological records are regarded which makes the estimation greater biologically realistic. However, in a complex version, the huge style of parameters to be envisioned is heaped huge than a clean version. Many such parameters are unknown, given the demonstrated instances of covid-19. Thus, it's going to boom the degree of uncertainty in model output. Therefore, in choosing an appropriate version, it's far important to have a balanced method among natural realism and decreasing uncertainties withinside the model predictions.

Thus, the modern-day deterministic SIR/SEIR fashions are envisioned with precaution. A consistent version that predicts the course of the epidemic is needed below those conditions. A greater correct model might be an extension of the classical SIR model for human-to-human transmission. The following 8 key tiers of infection can also be regarded i) suspected, ii) inflamed, iii) identified, iv) ailing, v) cured, vi) re-inflamed, vii) vulnerable, and viii) dead. It is crucial that the version distinguishes among identified and non-identified individuals because the former can also additionally responsibly isolate and decreases the unfold of contamination. Further, the duplicate style of covid-19 transmission needs to be differentiated on the way to seize the diverse healthcare offerings and have an impact on the lockdown measures throughout tremendous states and geographical provinces of India.

Front end developers could do numerous slip-ups that take away from the message they're hoping to pass on. For example, utilizing the erroneous shading plan should make it hard for the objective market to without issue parent the elements of qualification among a portion of the subjects. such an issue is obvious commotion. Contingent upon the dataset being demonstrated, customers for the most part struggle seeing the things which are comparative with one each other. At the point when pictured, customers find it difficult to part those things, which ability we should verify that we altogether show the significant records.

Another difficulty that incorporates imagining information is records misfortune. Regularly while we attempt to get rid of the seen commotion, we as a rule bring down the quantity of measurements being demonstrated. By doing this, a couple of records are lost. The requesting circumstances stood up to withinside the records handling are:

1. Big Data Challenge

COVID-19 infections keep to upward push and infected count increasing vigorously, and facts on the community degree at the prevalence of disease and cure inclinations are greater than ever. Volume of data keeps on expanding due to this big data problems occurred which causes issues in storage of data and visualization (Figure1). Data integration is certainly vital for purchasing the whole benefit from your large records. Data integration addresses the want for eliminating fact silos so that you can achieve deeper perception from massive records.

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Figure 1. Big data challenges



2. Data Sources

Finding an authorized and right records supply that gives all of the remember of instances in us of a with demise remember and lively remember is hard to get. The records desire to be updated.

3. Best Appropriate ML Model

Model preference is the gadget of choosing one in every of many candidate fashions for predictive modeling trouble. There also can be many competing issues whilst mode is used for appearing version choice beyond model performance, which includes complexity, maintainability, and to be had resources. The important training of version decision techniques is probabilistic measures and resampling techniques. Different fashions are there too are expecting the COVID-19 to unfold remember with extraordinary performance assessment. The performance assessment is as shown in Figure2.

SOLUTIONS AND RECOMMENDATIONS

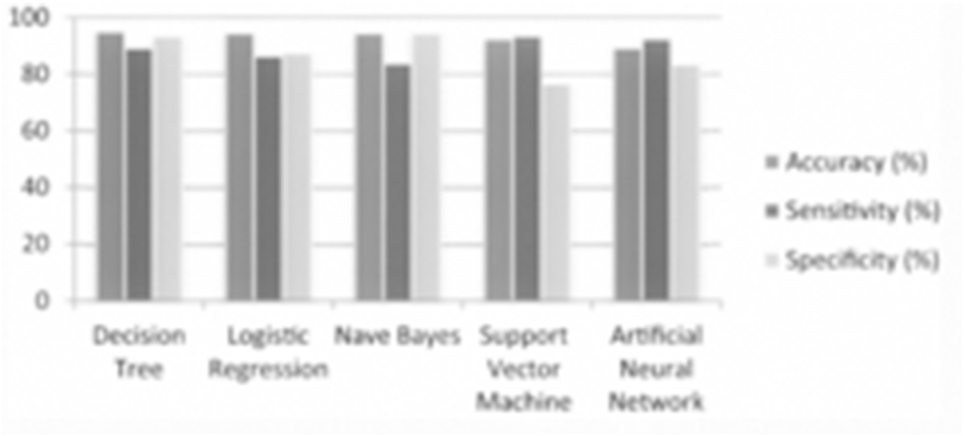
Tools and Techniques to Overcome Data Visualisation Problem

Data visualisation is the best way to visualise the data in format such as graph and bar. There are many tools available to visualise the data such as:

1. Google Charts
2. tableau

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Figure 2. performance evaluation



3. JS library

These tools can be used to visualise the data in some format such as bar graph line graph and different types of charts So data visualisation is a method to visualise the data in some like in the graphical format or in the diagrammatic form. While using graphical format the user should able to represent the data with suitable tooltips with all the required information on it such that these graph should convey the message of information to the end user. It gives us a clear idea about the data. data visualisation makes the people to visualise the data in some format or in some trends this type of data is more understandable than the big data so as people are naturally tend to understand the data in the format of some pattern instead of in the sheets. So as to visualise the data first of all we need to remove all the noise from the data so the data cleaning is performed on the data.

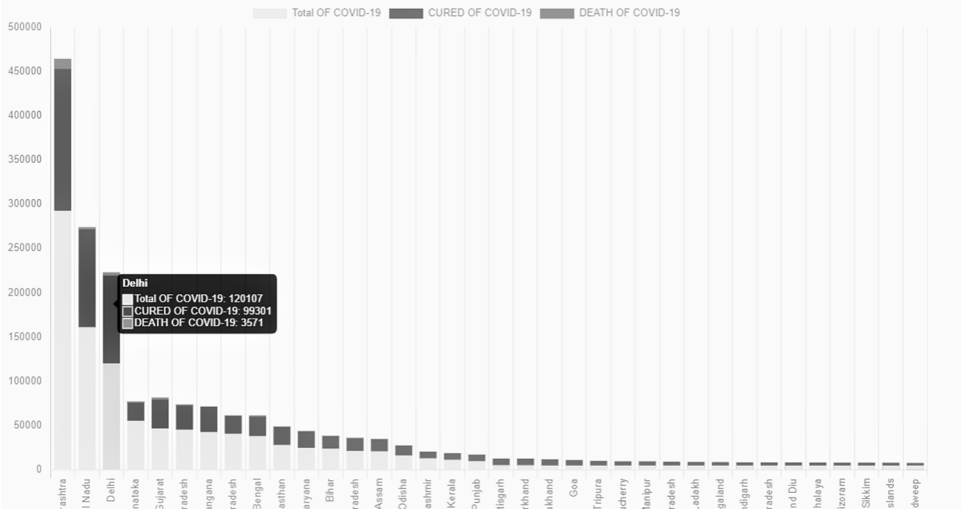
How to Build Charts Using Chart.js Library in JS?

To imagine information with graph. JS library in javascript follow the means given underneath:

Stage 1: Add chart. JS library to the HTML page in head section so we can utilize the library.
Stage 2: Chart. JS is a local area kept up open-source library that causes you easily imagine insights the utilization of JavaScript. It's like Chartist and Google Diagrams. It helps 8 interesting diagram types (counting bars, lines, pies), and they're all responsive. In various words, you set up your diagram once, and Outline. JS will do the hard work for you and make positive that it's continually decipherable (for example through putting off some uncritical subtleties if the diagram gets more modest)
Stage 3: Set up your information for visualisation. Chart. JS library expects the information which need to be as the clusters.
Stage 4: Characterize the kind of line. Begin Rewording Imagining realities with Diagram. JS is incredibly clear. We should simply characterize what format we need to draw, and avoid in the records that we need to picture.
Stage 5: Style the diagram with various styling alternatives.

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Figure 3. COVID Data visualized using bar graph



The covid count data will be visualized in different types of graphs like bar graphs or line graphs as shown in Figure 2.

Dashboard Implementation and ML Model

In this research work user will be using login functionality to login in the portal to view it visualised format of the covid count. So while registering for the portal user need to give the information for filling the form for registration to verify user email ID OTP will be send to respective mail ID so that verification can be done. To generate OTP we can use random number using random number function in JavaScript.

Data Fetching and Processing from API

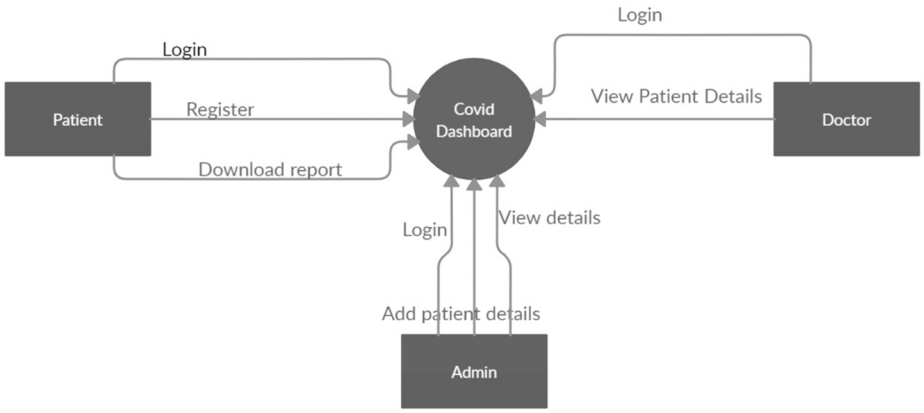
To get the covid count here post API will be used where the data will be in the JSON format. This data can be rendered using JSON object in Java. So as to fetch the API data in the JSON object we have to create one JSON object. For this we need to store the URL in the string format. Using URL class object we can convert the string into URL in Java. After that we have to form the HTTP url connection and need to read JSON data in that URL. In the API covid count will be stored in the form of the active count, confirm count and the death count. After fetching the count in an object we need to pass that object to the JavaScript page that is to front-end. So after getting the data in the JSON format we need to convert it into the array so that we can use it with the chart.js library to convert it into the graphical format.

For the information assets, POST Programming interface is utilized. Information is put away in JSON design in Programming interface. To get information from Programming interface JSON parsing strategies are utilized. Information in the Programming interface are forward-thinking. Convenient information will be there in Programming interface. Information will be envisioned through the graph. JS library in javascript. Diagram. JS is a local area kept up open-source library that causes you easily imagine insights the utilization of JavaScript. It's like Chartist and Google Graphs. It helps 8 remarkable outline types (counting bars, lines, and pies), and they're all responsive. In various words, you set up

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your graph once, and Diagram. JS will do the hard work for you and make positive that it's continually intelligible (for example through putting off some uncritical subtleties if the graph gets more modest). Programming interface is the abbreviation for Application Programming Interface, which is a product mediator that grants two capacities to talk about with one another. Throughout the long term, an "Programming interface" has regularly portrayed such an overall network interface to an application. All the more as of late, nonetheless, the cutting edge Programming interface has taken on certain characteristics that make them very prized and valuable:

Figure 4. DFD diagram



Current API's hold fast to prerequisites normally HTTP and REST, that are engineer cordial, without trouble available, and saw comprehensively They are managed more like product than code. They are intended for utilization for exceptional crowds (e. g., cell designers), they are archived, and they are formed such that clients can have uplifting assumptions for its security and lifecycle. Since they are a great deal of extra standardized, they have an unpleasant part more grounded discretion for security and organization, comparably checked and managed for execution and scale Like with any extraordinary piece of productized programming, the contemporary Programming interface has its own item improvement lifecycle (SDLC) of preparation, testing, building, administering, and framing. Also, present-day APIs are agreeably recorded for use and shaping.

Big Data Solutions

To store patients data amazon RDS (relational database system) Mysql is used as data is so vast it cannot be stored on local database. MySQL is that the world's most well-liked open-source on-line database and Amazon RDS makes it straightforward to line up, operate, and scale MySQL deployments within the cloud. With Amazon RDS, you'll be able to established ascendible MySQL servers in minutes with inexpensive and resizable hardware capability. Amazon RDS offers 2 SSD-backed storage picks for your MySQL information. General Purpose storage provides cheap storage for tiny or medium-sized workloads. the automated backup operation of Amazon RDS permits the healing of your MySQL information instance to any to consider time at intervals your distinct retention amount of up to 35 days. additionally,

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customers will operate user-initiated backups of your sound unit Instance. These full information backups are going to be kept by means of Amazon RDS until you expressly delete them.

With the coordination of man-made intelligence in records perception programming, a significant number of the inconveniences that huge information representation faces these days are being addressed. For instance, artificial intelligence can look at and advocate the quality ways to deal with imagine a dataset, and separate the information in a manner where representation can be accelerated. This tackles the difficulty of needing a specialist to break down and organize the insights for perception. Computer based intelligence can likewise outfit us with prescient investigation, which can improve dynamic and can show extra critical outcomes.

In this time of huge information perception, we at Worldwide Benefit Counseling Gathering are wanting to settle the greater part of the inconveniences that realities representation is managing today. We are by and by building up our own records representation apparatus alluded to as Moving Information that will permit you to now not exclusively envision your information, yet in addition to quicken time succession information. Sooner rather than later we are also looking to consolidate artificial intelligence into Moving Information to outfit you with focuses like prescient investigation and perception proposals.

Which Model will be Best Suited for Prediction?

Backing vector machine (SVM) is a learning set of rules this is getting utilized for relapse and arrangement examining undertakings. The early prognostic example of a pandemic of COVID-19 of every unbelievable soul should be known. However, the exact examination can likewise be a hard test. a path for the correct assessment of the SVM-focused COVID-19 framework is normally empowered sooner or later of this investigation. The prompted technique was once isolated into 3 fundamental layers: the insights arrangement layer, the pre-handling layer, and accordingly the product layer. the measure of data acquisition shall matches the records set basic for examination. regular skill investigation techniques rectangular measure used in the the pre-preparing layer to dispose of information inconsistencies. There rectangular measure two sub-levels inside the product layer, counting the amount of expectation and accordingly the level of examination of results, severally. The quick SVM strategy is referenced inside the utility layer to design the COVID-19 prognostic system. The angles and depictions of the purposeful technique for anticipating the ejection of COVID-19. It shows that {the knowledgeltheinfolthe information} framework layer incorporates realities enter for the neural organization, where the most recent Coronavirus pandemic used to be anticipated utilizing a managed acquiring information on rule. The factitious neural network comprises a lot of neurons that rectangular measure the quintessential unit of interaction data that distinguishes the separated construction, specifically the enter layer, the yield layer, and thusly the secret layer. The supervised technique to work area becoming more acquainted with to foresee the emission of COVID-19 is being integrated into this examination.

The records gathered through the information procurement layer is crude, because of the reality it would perhaps accept some fragmented boundaries and inconsistent information. furthermore, the skill is handled inside the pre-preparing layer. Anticipate missing values in this layer abuse moving normal sort, mean or mode, and decline clamor with standardization. each layer is divided into 2 sub-layers: the expectation and thusly the general execution layer, on the grounds that the interaction impacts rectangular measure additional submitted to the execution layer. A regulated machine dominating model perceived as Support Vector Machine (SVM) is utilized inside the expectation framework to prepare calculations. The dataset factors are addressed in a house in SVM and are separated into variables and organizations

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with comparative constructions that fall into indistinguishable partnerships, The information are viewed as p-dimensional for direct SVM that might be apportioned by the size of p-1 planes perceived as hyperplane. Therefore, the planes partition the arrangement of hindrances and record space among the data enterprises for relapse or order acquiring aptitude of adventure as demonstrated. The great option is picked dependent on the hole among the separated exercises. Therefore,the plane with the best limits among those two classes is perceived as the most edge publicity plane.

The n data point is defined as:

$$\left(\vec{x}_i, y_1\right),\ldots,\left(\vec{x}_n, y_n\right),\left(\vec{x}_i, y_1\right),\ldots,\left(\vec{x}_n, y_{n1}\right) \tag{1}$$

The genuine vector is addressed by x1x1 which can be either be -1 or 1,which is representingx_1. Hyper plane is assembled to diminish the distance somewhere in the range of $y-1$ and $y=1$ class, individually, which are characterized in Eq. (2) below:

$$\vec{w}.\vec{x}-b=0 \tag{2}$$

The normal vector is denoted by $\vec{w}$ while the offset of hyper place along $\vec{w}$ represented by $\frac{b}{\vec{w}}$ (2021).

SVM is perhaps the most well known Regulated Learning counts, which is used for Arrangement as agreeably as Relapse issues. Regardless, fundamentally, it is used for Characterization issues in AI. The inspiration driving the SVM estimation is to make a good line or assurance limit that can disconnect n-dimensional house into getting ready so we can without much of a stretch put the new data factor in the correct order later on. This enchanting decision limit is implied as a hyperplane. SVM picks the superfluous centers/vectors that help in making the hyperplane. These irrational models are called help vectors, and in this manner, the figuring is named a Help Vector Machine. Consider the under diagram where there are two unquestionable classes that are denoted the use of a decision limit or hyperplane. Rising levels of mortality are credited to their sending conduct through actual contact between people. It is incredibly indispensable to uncover the transmission of the pollution and furthermore to accept the early scopes of the disease so that the awesome planning of excellent careful steps can be taken. The present worldwide Covid pestilence (COVID-19) has acquainted new difficulties with established researchers.

Man-made consciousness (man-made intelligence)- roused procedures may likewise be valuable in foreseeing the conditions, outcomes, and ramifications of such an episode. These gauges may furthermore help to screen and prevent the unfurl of these episodes. This chapter proposes a prescient structure joining Backing Vector Machines (SVM) in the determining of a potential flare-up of Coronavirus. The discoveries bring up that the advised machine outflanks present-day draws near. The strategy should be utilized to anticipate the long haul unfurl of such an episode so we can place into impact proactive measures ahead of time. The discoveries of the investigations demonstrate that the SVM determining structure outflanked the Neural Organization techniques as far as precision and computational intricacy. The above constructed SVM framework model displays 98.8% and 96.8% outcomes in expressions of precision all through instructing and approval individually.

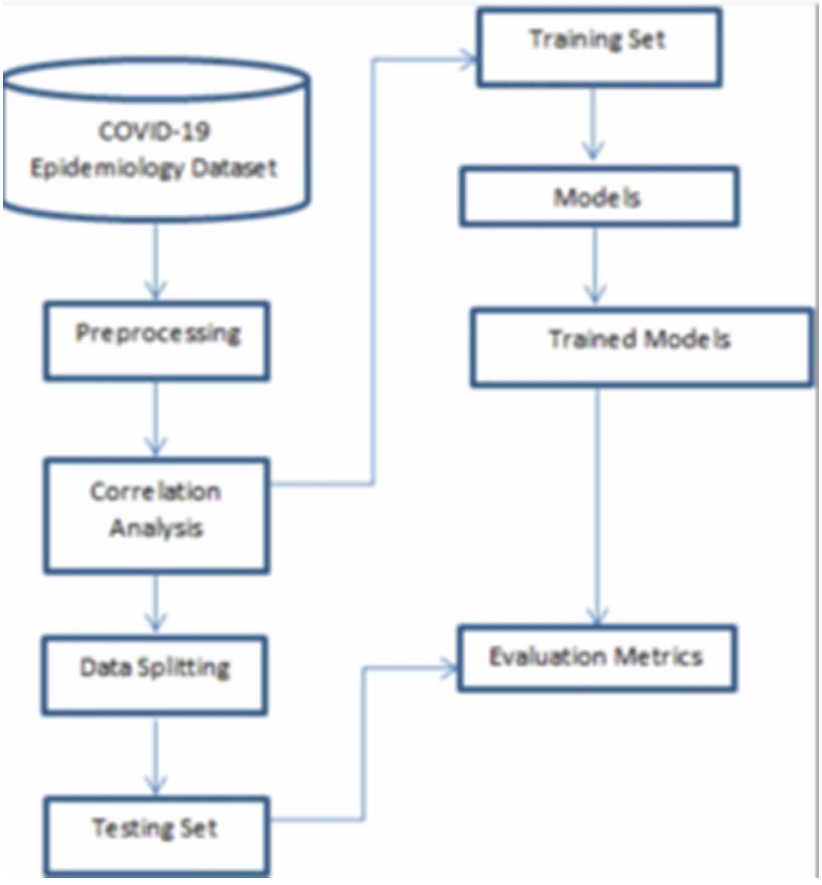
This learning is about the COVID-19 forecast additionally known as a novel coronavirus. In human life,COVID-19 used to be a threat. The fee of dying is elevating every day in India, contributing

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to hundreds of deaths. In order to unravel this pandemic power, the confirmed, and active instances nevertheless upward push day by means of day, this find out about objectives to estimate demise rates, the variety of lively cases and, cases of confirmed and the total that are recovered in the coming days. Prevision is produced via the use of approaches to computing devices gaining knowledge that is really useful in this respect. The dataset reports the day the pandemic began, tested cases, recovered cases, deaths, and active situations. To discover the details of recognized cases, rescued cases, death cases, the facts are originally pre-processed.

After the pre-processing step is done, the statistics are parted into two sets: an education set for the coaching model, and for trying out the mannequin check set is used. Learning models used are LASSO, SVM, decision tree, random forest regression, Linear regression. The techniques are educated randomly. Models are then evaluated with the assist of the following parameters like R2 score, mean absolute Error, Root Mean Square Error, mean rectangular error.

Figure 5. Data processing diagram



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FUTURE RESEARCH DIRECTIONS

Due to this Covid-19 global pandemic everybody's attention directed to the importance of health and life. The awareness is developing about fitness will truly lead to a raise in per capita expenditure on healthcare and will increase demand for healthcare merchandise and services.

We can provide the information about covid-19 related symptoms, preventions, travel safety. This in-turn will continue to multiply significant requirement for trained manpower in the Healthcare sector. In future the research work will add the functionality of the covid Epass which will generate the e pass for travelling purpose, at currently it's just showing the decision whether you can avail the Epass or not. These guidelines could help reduce the severity of the viral infection in covid-19 patients as well as elderly patients . From the reports of a small case series provided preliminary evidence that convalescent plasma therapy appears to be a safe and effective late-stage treatment for patients with COVID-19 infection. Therefore, Convalescent plasma therapy is highly recommended. We can provide a facility in our web application to help covid-19 patients to search for plasma such that if they need a plasma then they can search for plasma donator near area for that we need to take registrations from plasma donators through our web application. We would provide information of good hospitals and doctors nearby user if user will search for the same.

CONCLUSION

This concludes that the research work undertaken is to provide the web application which will facilitate the users with count of cured, deaths and active with the details about covid-19 patient reports in different formats. Users can not only download and share those reports in different formats but also able to know prediction of upcoming covid cases. A important environmental crisis ought to be sparked by using the hazardous of the COVID-19 pandemic. Researchers and authorities organizations round the world are involved that a tremendous percentage of the world's populace will be impacted by means of the pandemic. This study has used different ML techniques for the prediction of the COVID-19 outbreak globally. The dataset contains the past data, and the data is in the day, month, and 12 months format and make the prediction for upcoming days. SVM indicates the negative end result among along due to the fact of them up, and down in dataset values, it challenging to divide the values by a hyperplane. Therefore, the research projections can be a great gain for the human beings to take suitable steps, and to take rights to control the crisis of COVID-19. SVM model will be best suited for outbreak prediction .

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KEY TERMS AND DEFINITIONS

API: Application programming interface which communicate between user and software.

COVID-19: Disease caused by corona virus which affects respiratory system.

Data Fetching: Fetch is the retrieval of data by a software program, script, or hardware device. After being retrieved, the data is moved to an alternate location or displayed on a screen.

Data Prediction: "Prediction" refers to the output of an algorithm after it has been trained on a historical dataset and applied to new data when forecasting the likelihood of a particular outcome.

Dataset: Set of data or collection of data.

Mortality: The state of being subject to death.

nCoV: Another term for COVID-19.

Outbreak: A sudden or violent increase in activity.

Pandemic: Spread of a disease which affects the whole world.

Statistical Data: Collection of numerical data.

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APPENDIX

The intention of this appendix is to introduce JSP. Through examples, we will cover the fundamentals of JSP. The purpose is no longer to cover the whole lot about JSP, however alternatively to give a new programmer enough knowledge to start the use of JSP productively. We count on that you already have some fundamental Java and HTML knowledge. JSP is a simple Java-based particular for developing unique Sites. As an expansion of Java servlets, JSP used to be intended to work on the utilization of servlets. Therefore, JSP is advanced to deliver character-based yield to a customer, regularly an individual the utilization of an Internet browser. JSP is exclusively intended to work character-based yield. At the point when a JSP site page transforms into a servlet, that servlet is furthermore built to dispatch character-based yield. Since XML is 100% character-based, we have no need to do twofold tasks for this book. Advanced JSP programmers have a tendency to use servlets for nonvisual processing. An instance of this would be a controller page. These pages in no way display a result, but rather redirect visitors to different JSP pages. JSP pages can nevertheless be used to function nonvisual processing; servlets are simply a little more robust for this task.

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Chapter 10
Decision Support Proposal for Imbalanced Clinical Data

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ABSTRACT

The difficult diagnosis of acute appendicitis of patients appealing to the hospital with abdominal pain often leads to unnecessary acute appendicitis operations. Accordingly, the aim of this study is to be able to provide the correct diagnosis whether the existing case indeed necessitates operation or not through machine learning algorithms based on classification. To that purpose, SMOTE, random oversampling, and random undersampling methods were proposed to reduce the negative effects of imbalanced data set problem on classification, and it was benefitted from the risk factors in relation to Alvarado Score to predict the diagnosis of acute appendicitis. Additionally, a classification model was generated by using support vector machine classification algorithm. A decision support system was developed that could contribute to the decision making by generating interface for support vector machine algorithm in which the best performance was obtained.

INTRODUCTION

Acute appendicitis (AA) is the most common emergency in patients appealing to the hospital with abdominal pain in the healthcare field, and appendectomy (acute appendicitis surgery) is one of the first emergency operations worldwide (Andersson, Jaffe, & Berger, 2014). For this reason, the decision of whether the patient should be operated or not should be taken quickly. It is difficult to diagnose acute appendicitis. Negative appendectomy, which is determined as a result of the examination of the postoperative material, is seen to cause dozens of unnecessary operations and patients suffering due to the rate of encountering a disease-free appendix during surgery. A false negative diagnosis can delay the diagnosis and therefore increase morbidity, mortality and legal problems. (Flum & Koepsell, 2008). However, clinical diagnosis is often a challenge even for experienced surgeons. Negative appendectomy rate reaching 20-30% proves how difficult it is. (Yang, Wang, Chung, & Chen, 2006). It has been reported that the clinical diagnosis

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of acute appendicitis was correctly diagnosed in 78% of men and 58% in women. (Pieper, Keger, & Niisman, 1982). Many patients who underwent appendectomy were found to have negative histopathology of the surgically removed appendix, which is the gold standard for the diagnosis of appendicitis (Munir, Mushtaq, Ishaque, Mudassar, & Khalid, 2008). In the literature, it has been reported that the negative laparotomy rate for AA ranges between 4-75% (Eskelinen & Lipponen, 1992). In recent years, the decision of whether or not patients to undergo surgery poses a challenge with negative appendectomy rates of 10-25%, causing dozens of unnecessary operations (Hale, Moolloy, Pearl, Schutt, & Jaques, 1997). On the other hand, available statistics show that 1 out of 5 acute appendicitis cases were misdiagnosed and 40% of patients who underwent emergency appendectomy had a normal appendix (Kwok, Kim, & Gorelick, 2004). In another study, the possibility of encountering a negative laparotomy was reported to be between 13 and 36% (Bergeron, 2006). In another study, negative appendectomy rates of 3-30% of perforated appendicitis rates is seen (Binnebösel, Otto, Manhken, Gassler, & Schumpelick, 2009). It is seen in a different study that the negative appendectomy rates varied between 14.7% and 8.47% despite the advanced laboratory tests and imaging techniques in today's conditions (Seetahal, Bolorunduro, & Sookdeo, 2011). In another study, it is stated that the negative appendectomy rates determined as a result of the examination of the postoperative material are generally between 3-4% and 44% (Cleeve, Jones, Joshi, & Ward, Trends in Childhood appendicitis, 2011). Early surgical interventions without definitive diagnosis can result in a negative appendectomy rate of 20-30%, especially in women of childbearing age (DeKoning, 2016).

The removal of a normal appendix is a burden for both patients and healthcare resources (Khan, 2006). The increase in negative appendectomy rates can cause unnecessary morbidity and complications, and with the increase in treatment costs, physicians may face lawsuits (Liang, Andersson, & Jaffe, 2014).

Acute appendicitis appears to mimic many diseases such as acute abdominal pain, intestinal obstructions, gastroenteritis, acute cholecystitis, ureter stone colic, pancreatitis, diverticulitis, urinary tract infections, cystitis, lymphadenopathies, intestinal ischemia (Humes & Simpson, 2006).

This study emerged as a result of the mentioned reasons, negative appendectomy rates and interviews with specialist physicians.

The data sets of the patients in this study, which was carried out to reduce unnecessary AA operations due to misdiagnosis, bring about the class imbalance problem, which is frequently encountered in the field of health.

When much fewer instances of one class than the other class are observed in a binary-class dataset, the dataset is said to be imbalanced (Galar, Fernandez, & Tartas, 2012). In this study, SMOTE, Random Oversampling and Random Undersampling methods are proposed to reduce the negative effect of class imbalance problem on classification. In addition to the clinical signs of AA, many attempts have been made to identify ways to reduce the negative laparotomy rate. For example, laboratory measurements such as WBC count, percentage of neutrophils and CRP (C-reactive) are widely used as diagnostic aids in patients with suspected AA; however, diagnostic values are limited (Yang, Wang, Chung, & Chen, 2006). Some scoring systems have been created to reduce the negative appendectomy rate. These include clinical symptoms, physical findings, and laboratory tests, and assist the decision-making process if imaging tests are not available or approved (Escriba, Gamell, Fernandez, & Cubells, 2011). After reducing the imbalance problem in the data sets and stabilizing the data, the risk factors of Alvarado Score were used for the estimation of AA diagnosis. For this purpose, the Alvarado score was calculated and compared with the histopathological report result, which is accepted as the gold standard in the diagnosis of acute appendicitis. The class of a newly arrived patient data is determined by classification algorithms.

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Classification is an essential part of machine learning. In the classification, the data are divided into two parts as training set and test set. Model building is done in the training set and includes holdout, cross validation, bootstrap etc. Generalization of model results is provided with such techniques. Then, the performance of the model installed with the help of the test set is found (Zhang & Mani, 2003). Within the scope of this study, a Support Vector Machine model is created from classification algorithms. Python coding language is used for balancing methods and data analysis.

In this study, which was carried out through machine learning classification algorithms for the diagnosis of acute appendicitis, an interface was created for the Support Vector Machine algorithm, which was found to show the best performance, and a Decision Support System application was developed that could contribute to the decision-making mechanism of physicians. After the patient data is entered, the Support Vector Machine algorithm works in the infrastructure and helps the physician in deciding by giving the result that it should be intervened or observed according to the entered data.

The aim of this study is to determine the classification algorithm that makes the best way to distinguish whether a patient with abdominal pain is AA or not, thus preventing unnecessary surgery for many patients, and to create a Decision Support System for this purpose. It is also to examine the effect of solution algorithms on the performance of data mining methods when there is a class imbalance problem.

BACKGROUND

This section presents a review of the existing approach and a brief summary of the literature in the field of acute appendicitis.

Diagnosing acute appendicitis is an interesting challenge because it is difficult, and the decision must be made quickly. It has been reported that the clinical diagnosis of acute appendicitis was correctly diagnosed in 78% of men and 58% in women. (Pieper, Keger, & Niisman, 1982). In the literature, it has been reported that the negative laparotomy rate for AA ranges between 4-75% (Eskelinen & Lipponen, 1992).

This problem has attracted the attention of many researchers, and many computer systems have been studied to assist in diagnostic procedures (Philips, Wiles, & Schwartz, 1991). Early results of computer-aided diagnosis identified an overall diagnostic accuracy of over 90% (deDombaI, Leaper, Staniland, McCann, & Horrocs, 1972). However, an accuracy of 74% has recently been found (Adams, Chan, Clifford, & DeDombai, 1986), A 30% reduction in negative appendectomy rates has been reported. (Fenyö, 1987). In addition, some neural network algorithms have been used very successfully (Pesonen, Juhola, Ikonen, & Eskelinen, 1994).

Machine learning has made a great contribution to modern clinical decision making. Support Vector Machines, Random Forests and Artificial Neural Networks are supervised learning classifiers that are applied in complex clinical situations (Hsieh, Lu, Lee, & Li, 2011).

Lee at al. proposed PEL technique to reduce the majority-class instances by applying undersampling to provide balanced samples with 574 clinical cases provided in southern Taiwan. Their technique had better performance to find positive acute appendicitis than Alvarado system and reached area under the curve measure as 0.619 (Lee, Hu, Cheng, & Chuang, 2013) .

Hsieh at al. presented models that includes random forests, support vector machines, and artificial neural network to diagnose acute appendicitis. They collected 180 patients and achieved best performance by random forest. The performance of the sensitivity, specificity, positive, and negative predictive values of random forest were 94%, 100%, 100%, and 87%, respectively (Hsieh, Lu, Lee, & Li, 2011).

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Artificial Neural Networks has been a research area for the last 40 years The first computational, trainable neural networks were developed in 1959 by Rosenblatt (Rosenblatt, 1962) and Widrow and Stearns (Wwidrow & Stearns, 2003). The first ANNs were limited detectors in solving simple linear problems. Although the use of ANN in medicine is a new phenomenon, it has many applications such as diagnosis, imaging, pharmacology, pathology and of course prognosis.

ANN has been used in the diagnosis of appendicitis, low back pain, dementia, myocardial infection, psychiatric disorders, acute pulmonary embolism, and temporal arteries (Wei, Zhang, Barnhill, & Oesterling, 1998). Artificial neural networks have been used very successfully in many diagnostic problems (Bounds & Lyoyd, 1990). Artificial neural networks are computational models inspired by biological neural networks; The technique is considered strong in modeling nonlinear relationships and is increasingly applied in medical diagnosis and prediction (Lin, Wang, Liou, & Lai, 2008). A typical neural network consists of a series of processing units called sensors. In medicine, the most common type of neural network is a multilayer perceptron consisting of an input layer, several hidden layers and an exit layer. Each layer consists of several sensors. The sensors between the layers are heavily linked with different weights. Weights are adjusted by training algorithms. After the repetitive training cycle, the weights are adjusted to achieve the best predictive ability, like how the human learns from experience. Artificial Neural Networks are used in health areas such as heart attack early diagnosis and treatment, breast cancer early diagnosis and treatment, drug effects analysis, blood analysis classification, EEG, ECG, MR and quality enhancement. Artificial Neural Networks are a class of nonlinear mathematical models characterized by a complex structure of interconnected computational elements, neurons. These calculation items add a series of inputs using an aggregation operation and produce an output such as the severity of AA (Sargent, 2001).

Some authors have used artificial neural networks to develop predictive models to diagnose AA with varying degrees of success (Eberhart, Dobbins, & Hutton, 1991). Prabhudesai et al. Used artificial neural networks models with high accuracy results such as 100% sensitivity, 97% specificity, 96% Positive Prediction Rate to diagnose AA and detected 96% Negative Prediction Rate (Prabhudesai, Gould, Rekhraj, Glazer, & Ziprin, 2008). On the other hand, Hsieh et al. Showed that ANN was less successful with 94% sensitivity and 85% specificity (Hsieh, Lu, Chiu, & Li, 2011). In the study of Sakai et al., AUC analysis showed that ANNs gave a moderate result (Sakai, Kobayashi, Toyabe, Mandai, & Akazawa, 2007).

METHODS

Acute Appendicitis and Alvarado Scores

10% of admissions to emergency services are due to abdominal pain . The most common surgical cause in admissions with abdominal pain is acute appendicitis . Today, AA is one of the most common surgical emergencies and appendectomy is among the most common emergency operations worldwide . As AA is one of the most common surgical emergencies in the world, it affects 7% to 12% of the general population . The Alvarado scoring system is based on three symptoms, three symptoms, and two laboratory results. .

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Table 1. **The Alvarado scoring table for acute appendicitis**

		Alvarado Score
Symptoms	• Migration of pain to the lower right quadrant. • Nausea / vomiting. • Lack of appetite. • Sensitivity in the right lower quadrant. • Fever. • Rebound pain.	1 1 1 2 1 1
Laboratory findings	• Leukocytosis. • Neutrophil movement to the left (> 75%).	2 1
Total Score		10
Suggestions		
Alvarado Score: 0-4 = low, 5-6 = appendicitis possible and observation recommended, 7-8 = AA possibility and surgery recommended, 9-10 = highly likely AA and surgery recommended.		

Imbalanced Data Set

The real data sets used to diagnose many diseases that are rare in real life, especially in the health field, are not perfect. These data used to make predictions are often unbalanced. Therefore, due to the high probability of encountering unbalanced datasets in real life, the analysis of unbalanced datasets with machine methods has become an important issue(Liu & Zhou, 2009). Class imbalance is recognized as one of the ten challenging research problems in the field of data mining.

In a data set, the class with a higher number of observations is called the majority class, and the class with a low number of observations is called the minority class (Chawla, Bowyer, Hall, & Kegelmeyer, 2002). Generally, the minority class is the most striking and an important place in the field of study; therefore, an accurately high estimate of the minority class is expected (Liu & Zhou, 2009).

Traditional classification algorithms are designed to maximize overall accuracy by assuming a balanced class distribution independent of class distribution (He & Garcia, 2009). For this reason, when unbalanced data sets are shown to the algorithm, the effect of majority class observations is greater in the model established because they are generally suppressed by majority class samples (Thai-Nghe, GanDNer, & Schmidt, 2011). This causes the classifiers to over-fit and perform poorly, especially in the minority class. In addition, some observations belonging to the minority class cause misclassifications (Krishnaveni & Sobharani, 2011). Unbalanced datasets occur especially in medical diagnosis classification problems seen in health sciences (Mazurowski, Habas, Zurada, & Tourassi, 2008). Unbalanced data learning is one of the challenging problems in machine learning. Numerous solutions have been proposed to deal with the class imbalance problem, reduce or eliminate its effect (Guo, Li, Shang, Gu, & Gong, 2017). Some resampling methods used to overcome the class imbalance problem; Undersampling, Oversampling and Synthetic Minority Over Sampling (SMOTE).

ROS is the simplest and oldest method of dealing with unbalanced classification problems. In the random oversampling (ROS) method, the classifier is trained until the desired class ratio is reached, while it is used to balance the class distribution by randomly multiplying the minority class label samples to approximate the number of class labels (He & Garcia, 2009). Suppose S is an unbalanced data set, they

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are SNeg negative class (majority class) and SPoz positive class (minority class). The task of ROS is to randomly copy K samples from minority / positive class and add them to S, which ensures that the two classes in S have the same sample numbers. In this way, the sample number of the positive class is equal to SPoz ++ K, different K values correspond to different balance degrees for the training data set. When SPoz == SNeg, it means ROS is complete. Although ROS is an effective method, excessive compliance problem may arise because it takes exact copies of minority class samples (Chawla, Bowyer, Hall, & Kegelmeyer, 2002).

It is a non-intuitive method that aims to balance class distribution by randomly eliminating majority class instances in random under-sampling (Baesens, Vlasselaer, & Verbeke, 2015). he random under-sampling approach reduces F negative samples to the S value. Different F values correspond to different degrees of balance for the training data set after RUS processing. When SNeg-F == SPoz, RUS operation is completed. The biggest disadvantage of RUS is that potentially useful samples can be discarded.

One of the methods developed to reproduce the education data in the minority class by approximating it to the majority class in order to obtain a more reliable classification result is the SMOTE algorithm. To overcome the weakness of ROS; The synthetic minority oversampling technique presented by Chawla et al. Is a simple, effective and widely used class balancing method(Chawla, Bowyer, Hall, & Kegelmeyer, 2002). SMOTE intervenes among existing minority samples to create new examples of artificial minorities. Therefore, the SMOTE algorithm is a class balancing method that tries to find a new potential sample between two close real positives (Chawla, Bowyer, Hall, & Kegelmeyer, 2002). Suppose the number of positive samples after oversampling should be a multiple of the original sample number (m ++ 1) .For each positive sample xPoz i (i∈ [1, 2, ……, SPoz], xPoz-Near ik (k == 1, It needs to find the nearest positive sample neighbors, denoted as 2, Number of artificially new positive samples m x SPoz (Sun, Lang, Fujita, & Li, 2018).

$$x^{\text{Poz-SMOTE}}_{ik} = x^{\text{Poz}}_{i} + \text{rand}(0,1) \times (x^{\text{Poz-Near}}_{ik} - x^{\text{Poz}}_{i}) \; (i \in [1, 2, \ldots, m]) \quad (1)$$

In the above formula (1), the function rand (0,1) produces random values between 0 and 1. New replicated positive samples and original positive samples will be used together as training positive samples. The number of artificially reproduced positive samples varies according to different values of m; this leads to balance degrees between positive and negative grade in the final training dataset.

Support Vector Machine (SVM)

SVM was discovered in 1992 by Boser et al. (Boser, Guyon, & Vapnik, 1992). SVM has been used in the solution of problems related to regression and classification in recent years. SVM uses kernel functions with high dimensional properties to ensure high performance when performing classification. Compared to other classification algorithms, SVM has been observed to classify more successfully. The main purpose of SVM is to find a hyperplane that can optimally separate classes from attributes. The most important difference of SVM from other linear methods is that it offers solutions to minimize the possibility of making mistakes when classifying test data (Boser, Guyon, & Vapnik, 1992).

SVM is one of the well-known methods proposed for separating nonlinearly separable classes (Han & Kamber, 2006). Today, SVM shows great success in biological applications, cancer morphology in medicine, determination of treatment success and related gene, diagnosis of various diseases (diabetes, breast cancer, thyroid disease and heart diseases, etc.) (Guyon, Weston, Barnhill, & Vapnik, 2002).

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The concept of dividing classification points into three dimensions using a line or hyperplane is also used in other machine learning techniques. However, in SVM, the technique by which the hyperplane is chosen is different. The following function is used to maximize the hyperplane (Cortes & Vapnik, 1995),

$$f\left(\vec{x}\right)=sgn\left(\sum_{i=1}^{n}y_i\alpha_i.\,K\left(\vec{x},\vec{x}_i\right)+b\right) \tag{2}$$

where y is the output variable, b is bias, and α is obtained from solving the following equation on each. input:

$$\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{i=1}^{n}a_ia_j.\,y_iy_j.K\left(\vec{x}_i,\vec{x}_j\right) \tag{3}$$

where the corresponding a_i is greater than 0, x_j are named support vectors.

Linear Separability

Suppose there is $\left(x_1,y_1\right),\left(x_2,y_2\right)\ldots\left(x_n,y_n\right)$ D dataset. Here n y ∈{+1,-1} is assumed and is the number of elements of the data set. The $\vec{x}_1$ of each example is expressed as the m-dimensional real vector, and the class information that these examples have is shown as y_i. The set of classes that each instance can belong to is labeled as -1 or +1. The examples in the D data set and the classes to which these examples belong are shown as follows (Furey, Cristianini, & Haussler, Support vector machine classification and validation of cancer tissue samples using microarray expression data, 2000):

$$D=\{\left(x_i,y_i\right)|x_i\in R^n,y_i\in\left\{-1,1\right\}\}_{i=1}^{l} \tag{4}$$

$$X=\begin{bmatrix}\vec{x}_1\\ \vdots\\ \vec{x}_n\end{bmatrix}\in R^{nxm}ve\vec{y}=\begin{bmatrix}y_1\\ \vdots\\ y_n\end{bmatrix}\in\left\{-1,+1\right\}^n \tag{5}$$

There can be an infinite number of hyperplanes that divide the training data set into two. To achieve the widest distinction between the two classes, the SVM algorithm chooses the hyperplane with the largest margin within this hyperplane. Due to the hyperplane selection with the widest margin, the generalization feature of the SVM algorithm is increased. Many hyperplanes can be used to separate data sets from each other. The most convenient way is to choose those that have the largest margin between the two hyperplanes.

Let the data set in the learning problem belong to two different classes shown as -1 and +1. In this case, our training set can be represented as $D=\{\left(x_i,y_i\right)|x_i\in R^n,y_i\in\left\{-1,1\right\}\}_{i=1}^{l}$. Here $\vec{x}_i$ in the data set i. The vector shows the label of the class to which this vector belongs in y_i. The inner product of two

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vectors $\vec{w}^T\vec{x} = \sum_i w_i + x_i$ is used in defining the linear classifier function. The linear classifier is shown in the figure below based on the linear discriminant function:

$$f\left(\vec{x}\right) = \vec{w}^T\vec{x} + b \tag{6}$$

In this equation, w$\vec{}$ is the weight vector and *b* is the constant value of how far the hyperplane is from the origin. In this case, the hyperplane is defined as follows:

$$\left(\vec{x}\right) = \vec{w}^T\vec{x} + b = 0 \tag{7}$$

It turns into a discriminant function that divides the space containing the training data set into two. The target qualities of the samples are assigned according to the region they are located according to this hyperplane in the training space. The sign of the classifying equation indicates the target class of the sample vector.

$$y_m = \begin{cases} 1, & \vec{w}^T\vec{x} \geq 1 \\ -1, & \vec{w}^T.\vec{x} \leq 1 \end{cases} \tag{8}$$

The two expressions in Eq. 8 can be converted into a single equation and written as:

$$y_i\left(\vec{w}^T.\vec{x} - b\right) \geq 1 \tag{9}$$

Primal Form

In geometry, the distance between two parallel planes is found by $\frac{2}{\|w\|}$. The purpose of the SVM classification algorithm is to find the classifier hyperplane parallel margin far apart from each other. In this case, an optimization problem arises.

The aim here is to maximize the expression $\frac{2}{\|w\|}$. This maximization problem, ‖ w ‖ It can also be expressed as a minimization of the expression. This expression can be further developed and converted to $\frac{1}{2}\|w\|^2$ in a way that the solution remains unchanged. In this way, our optimization problem can be transformed into a quadratic optimization problem. The new optimization problem will be:

$$w = \arg\min_{w \in R^m} \frac{1}{2}\|w\|^2, \quad kIsIt : y_i\left(\vec{w}^T.\vec{x}\right) \geq 1, \quad i = 1, \ldots, n \tag{10}$$

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This equation turns into a quadratic function minimization problem with linear constraints. Lagrange function is used to solve this problem.

$$f\left(x_1,\ldots,x_n\right)$$

$$g_i\left(x_1,\ldots,x_n\right)=b_i,\quad i=1,\ldots,m,\quad m<n \tag{11}$$

Let there be a maximization problem for the function shown in Equation 11. Using the Lagrangian multipliers $\left(\alpha_{i,}, i=1,\ldots,m\right)$, the lagrange function will be as follows.

$$\mathcal{L}\left(x,\alpha\right)=f\left(x\right)+\sum_{i=1}^{m}\alpha_i\left(b_i-g_i\left(x\right)\right) \tag{12}$$

Quadratic function minimization problem with linear constraints in SVM classification algorithm using Lagrangian function will be as follows:

$$\mathcal{L}\left(\vec{w},b,\alpha\right)=\frac{1}{2}\left\|w\right\|^2-\sum_{i=1}^{n}\alpha_i\left(y_i\left(\vec{w}_i.\vec{x}_i+b\right)-1\right) \tag{13}$$

In the optimization problem transformed to Lagrangian function, $\mathcal{L}$, and *b* values need to be found for the hyper correction that separates the space where the training set is. For this, lagrange function $\mathcal{L}$ should be differentiated with respect to *w* and *b* respectively.

$$\frac{\partial\mathcal{L}\left(\vec{w},b,\alpha\right)}{\partial w_i}=0,\quad i=1,\ldots,n,\quad \vec{w}=\sum_{i=1}^{n}a_i y_i\vec{x}_i \tag{14}$$

$$\frac{\partial\mathcal{L}\left(\vec{w},b,\alpha\right)}{\partial b}=0,\quad i=1,\ldots,n,\quad 0=\sum_{i=1}^{n}a_i y_i \tag{15}$$

Kernel Trick for Nonlinear Classifier

If a data set cannot be parsed linearly, a linear hyperplane cannot be found that can separate classes. In this case, in order to find a nonlinear classifier function, for the data set that cannot be parsed linearly, the linear SVM classification algorithm must be converted to a nonlinear SVM classification algorithm.

The kernel function helps to split data points in a higher dimensional space if they are not separated at a lower dimension. However, projecting points in a higher dimension can lead to the curse of dimensionality.

Frequently used kernel functions in the literature are linear, polynomial, sigmoid and radial based kernel functions.

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Linear kernel function is the most basic function. It consists of the dot product of the vectors $\vec{x}_i$ ve $\vec{x}_j$ and the constant *c*.

$$K\left(\vec{x}_i, \vec{x}_j\right) = \vec{x}_i, \vec{x}_j + c \tag{16}$$

Polynomial based kernel functions are particularly suitable for situations where the data set used in education is normalized.

$$K\left(\vec{x}_i, \vec{x}_j\right) = \left(s\vec{x}_i, \vec{x}_j + c\right)^d \tag{17}$$

The sigmoid kernel function is also referred to in the literature as the hyperbolic tangent kernel function and the multilayer perceptron kernel function. The Sigmoid core function has come from artificial neural networks into the support vector machine domain. It is used as an activation function in artificial neural networks.

$$\left(\vec{x}_i, \vec{x}_j\right) = \tanh\left(s\vec{x}_i, \vec{x}_j + c\right) \tag{18}$$

The Radial Based Kernel Function is quite similar to the gaussian kernel function. Square expression in the norm has been removed.

$$K\left(\vec{x}_i, \vec{x}_j\right) = e^{\frac{\left\|\vec{x}_i - \vec{x}_j\right\|}{2\sigma_0}} \tag{19}$$

DATASET AND ANALYSIS

Dataset

All clinical data of 1454 patients who applied to the hospital with the complaint of abdominal pain and were operated with a pre-diagnosis of acute appendicitis were obtained from different hospitals. The anamnesis (history), physical examination findings, biochemistry laboratory test results and epicrisis reports of the patient were retrospectively taken from the databases of all hospitals. The data obtained in this study is the highest data that can be collected so far. Because acute appendicitis is a rare disease.

Risk factors of the Alvarado score, which are used to estimate the risk of acute appendicitis, were used. According to the Alvarado score, data were obtained from anorexia, nausea or vomiting, displacement of pain from the periumbilical region to the right lower quadrant, tenderness in the right lower quadrant, fever and rebound pain. According to literature studies, having a body temperature above 38ºC was accepted as high fever. By scanning laboratory findings, leukocytosis (WBC) and neutrophil percentage (NE%) values were recorded. According to the Alvarado score, the lower limit for WBC was 10,000 / mm3 and the lower limit for the neutrophil percentage was 75% for neutrophilia. WBC and NE% values

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were used numerically while applying machine learning algorithms. The pathology reports of all patients were examined and histopathologically diagnosed with acute appendicitis were recorded as 0 and those who did not. In addition to these, age and gender findings of all patients were added to the data and it was determined whether these two characteristics influenced the classification.

Various methods are available for the diagnosis of acute appendicitis. In this study, machine learning algorithms, which are sub-branches of artificial intelligence, were used against the Alvarado score. Since the patient data used are unbalanced data sets, Random Oversampling, SMOTE and Random Undersampling methods, which make the data balanced, were used in data pre-processing. Support Vector Machine algorithm, one of the classification algorithms, was used.

Evaluation

Table 2. Attributes used for prediction

ATTRIBUTES USED FOR FORECAST (INDEPENDENT VARIABLES)		
Attribute Name	**Data Type**	**Coding Type**
Migration of pain to the lower right quadrant	binary	1: Yes, 0: No
Lack of appetite	binary	1: Yes, 0: No
Nausea / vomiting	binary	1: Yes, 0: No
Sensitivity in the right lower quadrant	binary	1: Yes, 0: No
Rebound pain	binary	1: Yes, 0: No
Fever	binary	>38: 1: Yes, <38: 0: No
Leukocytosis (WBC)	Numerical	
Neutrophil movement to the left (NE%)	Numerical	
Age	Numerical	
Gender	binary	1: Man, 0: Women
DEPENDENT VARIABLE		
Appendicitis Diagnosis	binary	0: Negative-AA+ 1: Positive-AA-

The results obtained as a result of the classification are expressed with the complexity matrix (confusion matrix) or the complexity table. The actual and predictive classes of the data classified in this matrix are shown. The columns of the results obtained as a result of classifying rows of the matrix show the actual values. The complexity matrix of the two classes is presented in Table 3 (Han & Kamber, 2006).

The confusion matrix is used to calculate many common classification criteria. In machine learning, there are various measures that measure the performance of the model established in classification methods. It is calculated by making use of the 2x2 classification table given below for the case of dual classification. Some of these are as follows:

- Overall accuracy
- Sensitivity
- Specificity

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- Area Under Curve (AUC)
- F-Measure

The TN in the complexity matrix table indicates the number of samples that are actually acute ap-

Table 3. An example complexity matrix created for two classes

		Predicted Class	
		Negative (AA+) Surgical Operation Should Be Performed	**Positive (AA-) Must be observed**
Actual Class	Negative (AA+) Surgical Operation Should Be Performed	True Negative (TN)	False Positive (FP)
	Positive (AA-) Must be observed	False Negative (FN)	True Positive (TP)

pendicitis and are labeled as acute appendicitis as a result of classification, TP indicates the number of samples that are actually labeled as non-acute appendicitis and not acute appendicitis as a result of classification. FP is actually acute appendicitis and indicates the number of samples labeled as non-acute appendicitis as a result of classification. FN is not actually acute appendicitis but indicates the number of specimens labeled as acute appendicitis as a result of classification.

In this study, accuracy, sensitivity, precision, F-criterion and area under the ROC curve (AUC) criteria were used while evaluating the model success.

Accuracy

The correct classification rate of the data in the test set of the model created using the training set is called accuracy. It helps to evaluate the overall performance of the classifier. However, the accuracy criterion is not enough if there is an uneven distribution in the data set. Because the accuracy criterion is affected by the prevalence of data. For example, diagnosing all subjects with no disease in a population with a disease prevalence of 3% with a diagnostic test provides an overall accuracy rate of 97%. However, this test cannot distinguish patients from healthy individuals. Accuracy is found by dividing the number of correctly estimated and classified data by the total number of data. The accuracy criterion is calculated with the equation in Equation 20 for a case of two classes.:

$$Accuracy = \frac{TP + \mathrm{T}N}{TP + \mathrm{T}N + \mathrm{F}P + \mathrm{F}N} \tag{20}$$

It is stated in various sources that the accuracy ratio should not be used in class imbalance *(Kararağaoğlu, Karakaya, & Kılıçkap, 2016)*. Accuracy ranges from zero to one. If this value approaches one, it shows that class success is high.

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Recall

Recall is the probability that a sample that is negative in the real situation will also turn out to be negative as a result of the estimation (Han & Kamber, 2006)

The test is called the discrimination of the sick from the sick. In other words, it shows how many of the patients with acute appendicitis were correctly predicted by the model *(Larose, 2014)*. Recall is calculated as in Equation 21:

$$Recall = \frac{TN}{TN + \mathrm{F}P} \tag{21}$$

Sensitivity

Sensitivity is the probability of a positive sample in the real situation as a result of the estimation (Han & Kamber, 2006). It is called "recall" in the results showing the classification performances.

It is the ability of the test to distinguish between those without acute appendicitis and those without acute appendicitis. That is, how many of the patients who do not actually have acute appendicitis are correctly predicted by the system (Larose, 2014). Sensitivity is calculated as in Equation 22:

$$Sensitivty = \frac{TP}{TP + \mathrm{F}N} \tag{22}$$

Both sensitivity and specificity can be used to evaluate classification performance with unbalanced data. In data groups with unbalanced data distribution, it is desirable to have high sensitivity and selectivity as much as possible (Sokolova, Japkowicz, & Szpakowics, 2006).

Precision

Precision is the value that gives the correct class to which a positive sample is assigned by the model. It is the ratio of the number of samples correctly classified as non-acute appendicitis to the total number of samples classified as non-acute appendicitis by the model (Larose, 2014). Precision is calculated as in Equation 23:

$$\mathrm{Precision} = \frac{TP}{TP + \mathrm{F}P} \tag{23}$$

F-Measure

While calculating the F-Criterion classification performance criteria, the calculation of precision or sensitivity alone may be incomplete. The F-criterion value represents the harmonic mean of precision and sensitivity values. The F-criterion value is between zero and one, and higher F-criteria values indicate high classification performance (Sokolova, Japkowicz, & Szpakowics, 2006).

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$$F-\text{Measure}=2*\frac{\text{Sensitivity}*Precision}{Sensitivity+\text{Precision}} \tag{24}$$

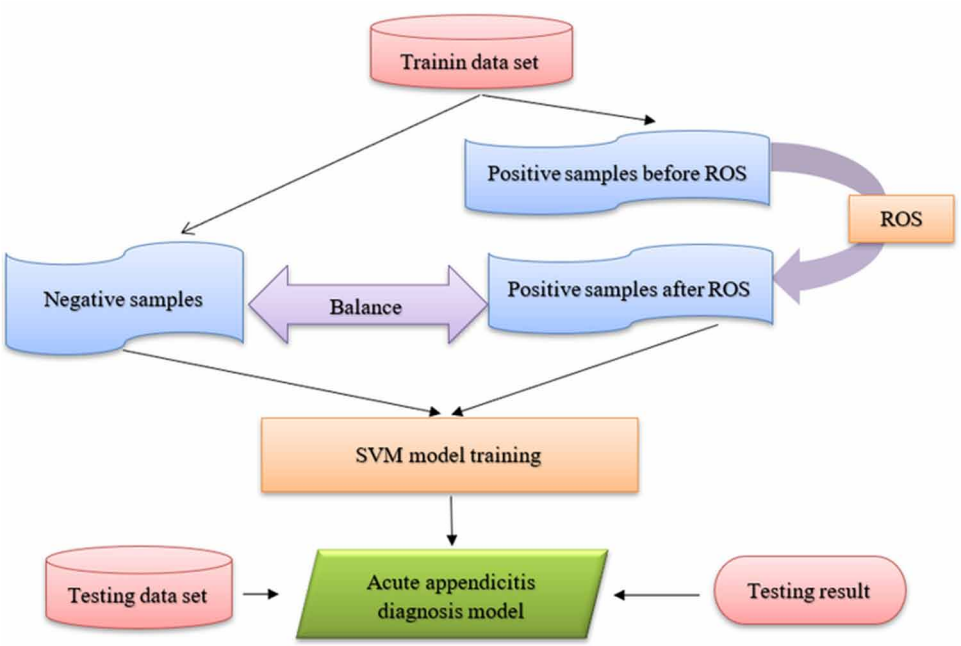
Area Under the ROC Curve (AUC)

The AUC metric representing the area under the ROC curve is frequently used to test the performance of classifiers. The above-mentioned ROC curve is a curve drawn between points (0,0) and (1,1). AUC representing the area under this curve takes values between 0 and 1. When the AUC value approaches 1, the classifier makes correct predictions, the value 0.5 indicates that the classifier makes random predictions and the values close to 0 indicate that the classifier makes false predictions (Kararağaoğlu, Karakaya, & Kılıçkap, 2016).

SOLUTIONS AND RECOMMENDATIONS

The flow chart of the ROS-SVM model for diagnosis of acute appendicitis is shown in Figure 1.

Figure 1. The flow chart of ROS-SVM model for diagnosis of acute appendicitis (Sun, Lang, Fujita, & Li, 2018).



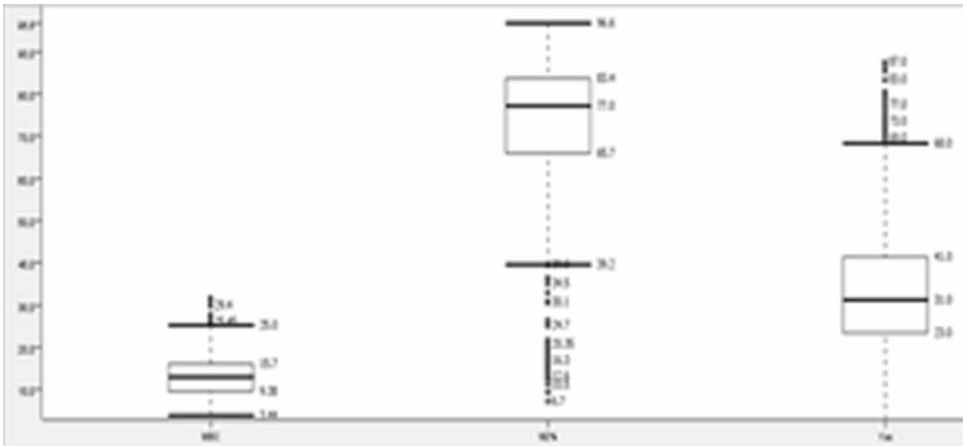
Statistical information about the qualifications is shown in Table 4. No missing value has been determined for the data.

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Table 4. Descriptive statistics of attributes in the dataset

Attribute Name	Min	Max	Mean	Std. Deviation	Variance	Skewness	Kurtosis	Median
Migration of pain to the lower right quadrant	0	1	0.957	0.204	0.041	-4.491	18.191	1
Sensitivity in the right lower quadrant	0	1	0.93	0.255	0.065	-3.37	9.367	1
Rebound pain	0	1	0.756	0.43	0.185	-1.192	-0.579	1
Lack of appetite	0	1	0.403	0.491	0.241	0.396	-1.846	0
Nausea / vomiting	0	1	0.423	0.494	0.244	0.312	-1.905	0
Fever	0	1	0.208	0.406	0.165	1.437	0.066	0
Age	0	87	32.979	14.549	211.662	0.688	0.555	31
WBC	3.44	31.25	12.785	4.543	20.638	0.500	0.251	13
NE%	6.7	96.6	71.821	17.991	323.665	-1.744	3.182	77
Gender	0	1	0.391	0.488	0.238	0.446	-1.804	0

Figure 2. Box plot of WBC, NE% and age attributes



Box plot is shown in Figure 1 to obtain information about the possible endpoints of numerical properties. When Figure 1 is examined, at first glance, the presence of extreme values of WBC, NE% and age attributes in the data set shows that the values of the attributes are in different ranges.

Class Balancing Methods

The data set in this study consists of 1454 patients. According to histopathological reports, 1294 patients with acute appendicitis were labeled as 0 and 160 patients without acute appendicitis were labeled as 1. The distribution of the high imbalance data set is shown in Figures 3 and 4. In our study, SMOTE, ROS and RUS algorithms were proposed to reduce the negative effect of class imbalance problem on classification.

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Figure 3. Class distribution histogram

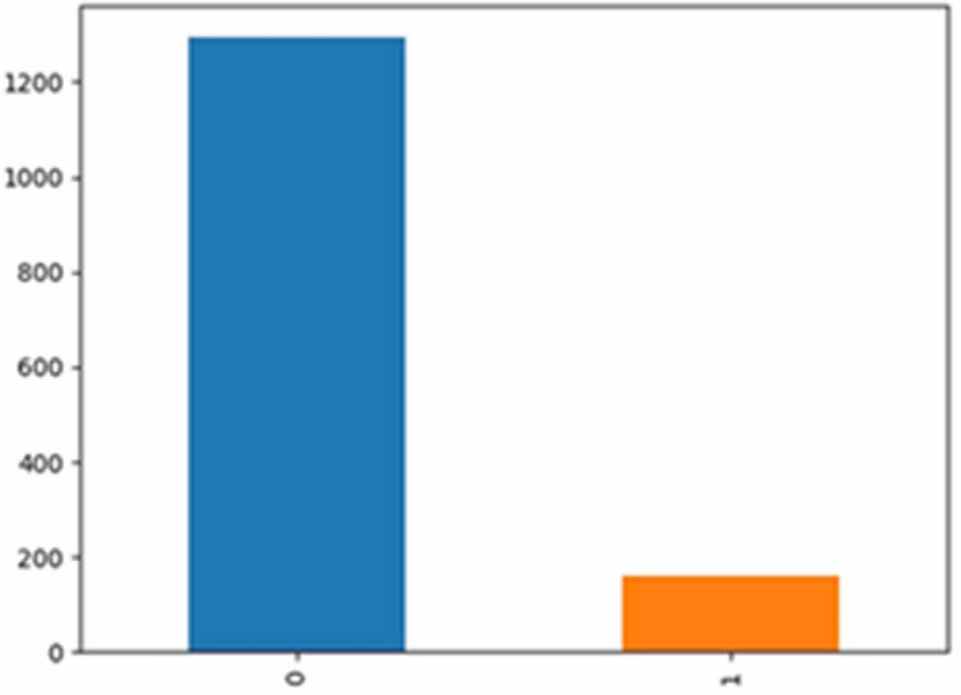
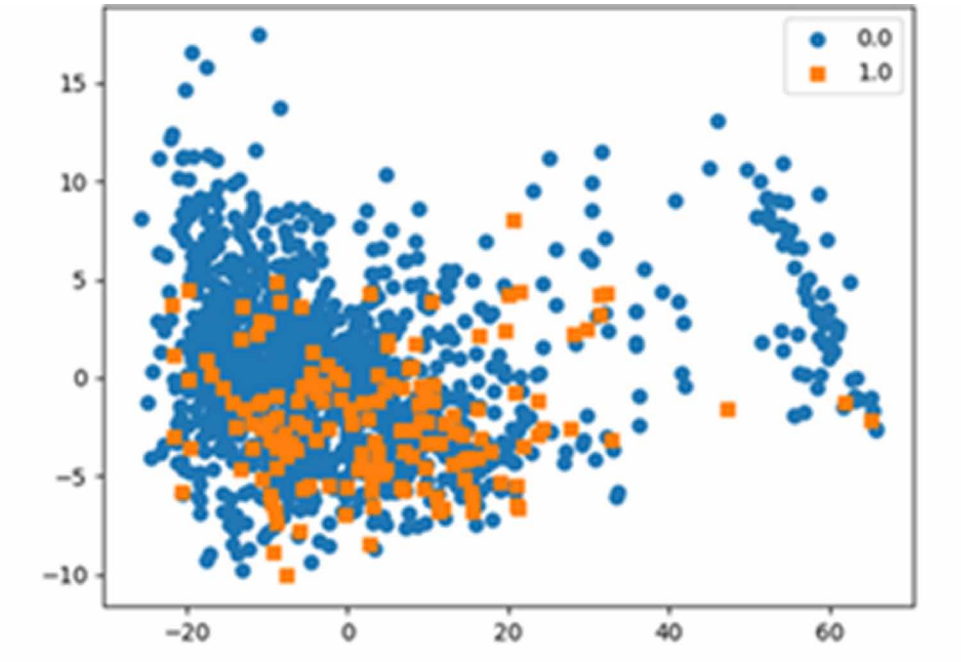


Figure 4. Class Distribution with PCA



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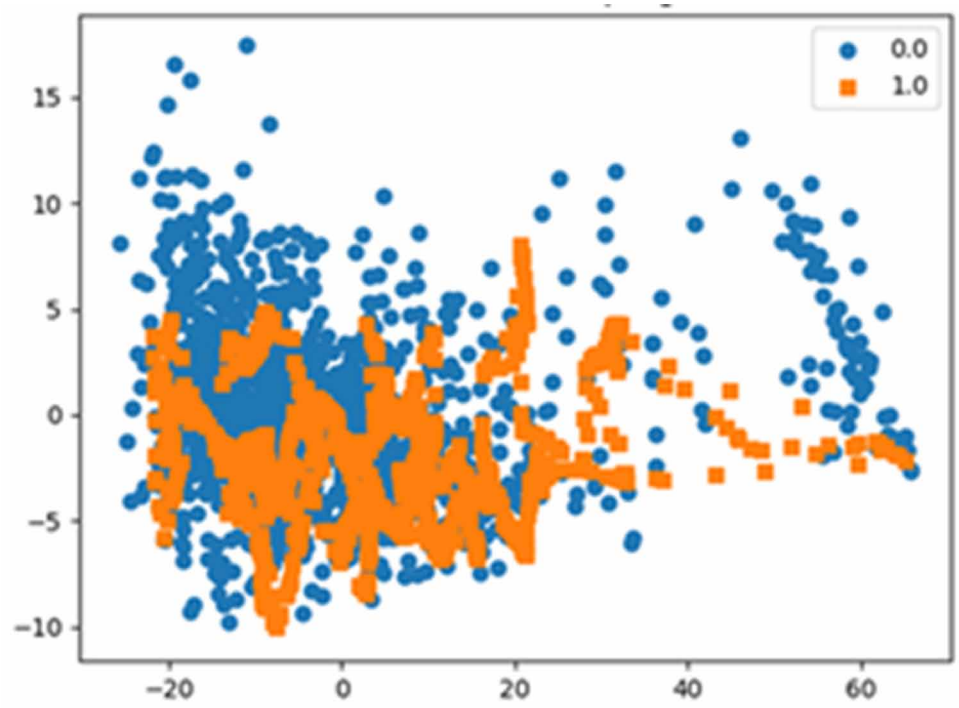
Random Over Sampling (ROS)

In the random oversampling (ROS) method, the classifier is trained until the desired class ratio is reached, while it is used to balance the class distribution by randomly multiplying the minority class tag samples to approximate the number of class tags. 160 minority class tags labeled 1 are approximated to 1294 majority class labels labeled 0.

Original data distribution: ((0: 1294, 1: 160})
Resampled data distribution: ((0: 1294, 1: 1294})

Figure 5 indicates the data distribution after the ROS method.

Figure 5. Random oversampling data distribution

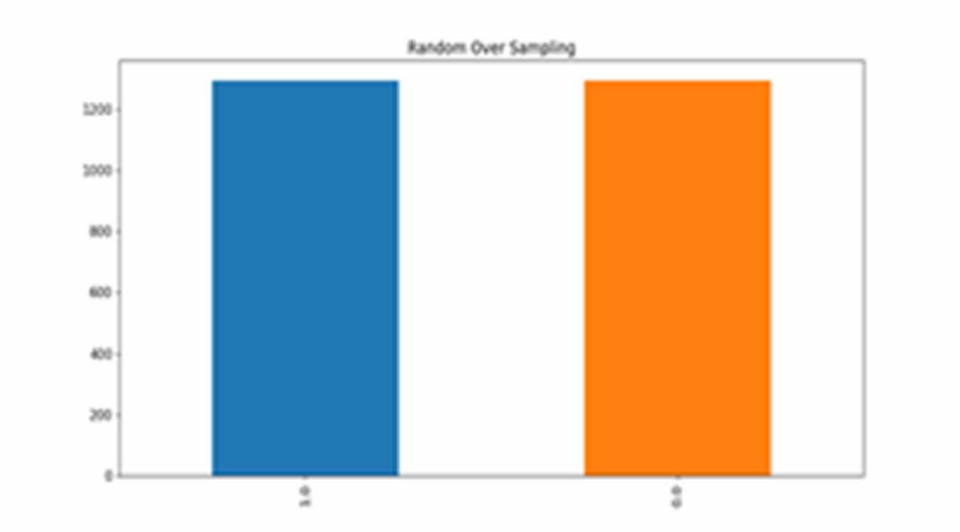


SMOTE

SMOTE intervenes among existing minority samples and creates new artificial minority samples. The basic assumption is that there is an artificial positive sample between two close real positive samples. Therefore, the SMOTE algorithm is the class balancing method used artificially between two real positive samples that are close to each other. 160 minority class tags labeled 1 are approximated to 1294 majority class labels labeled 0.

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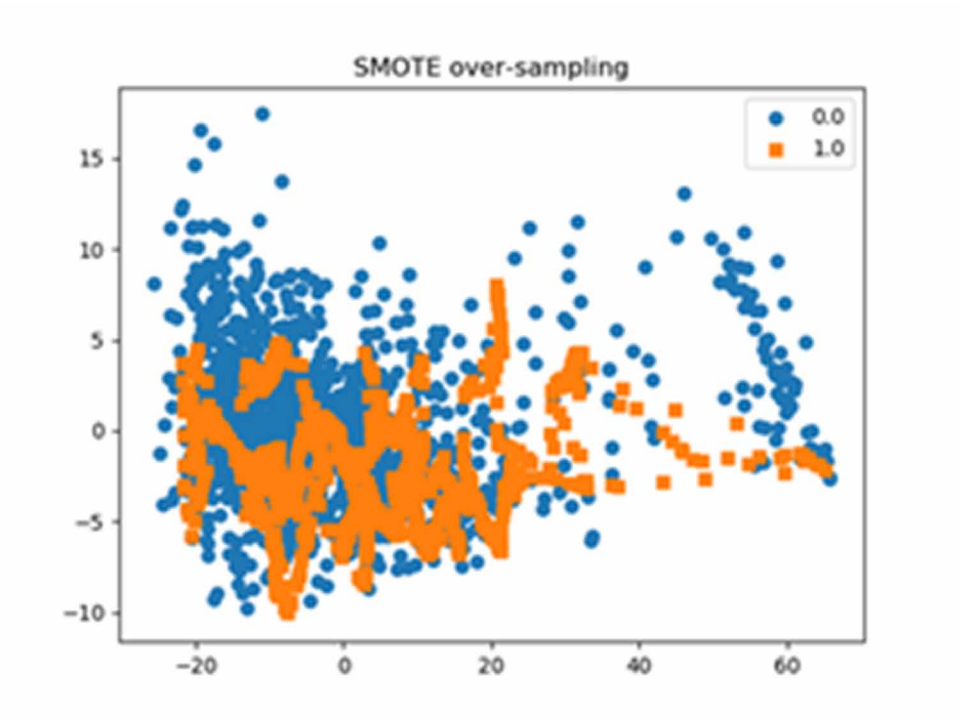
Figure 6. Random oversampling data distribution histogram



Original dataset distribution: ((0: 1294, 1: 160})
SMOTE dataset distribution: ((0: 1294, 1: 1294})

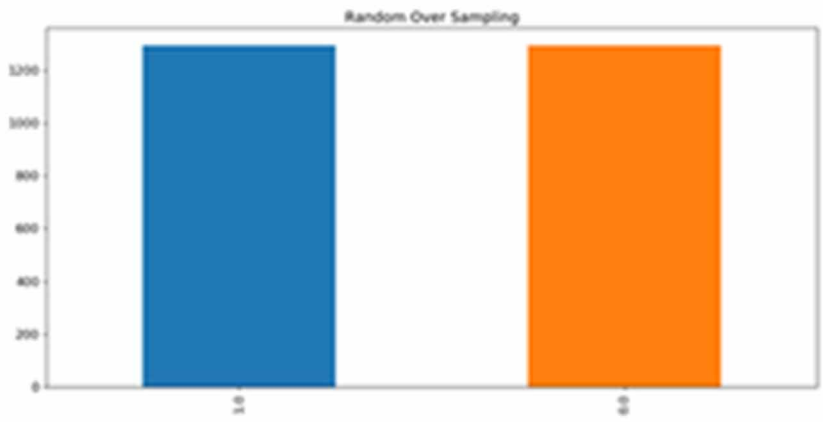
Figure 7 shows the data distribution after the minority class is approximated to the majority class.

Figure 7. SMOTE dataset class distribution with PCA



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Figure 8. SMOTE dataset class distribution histogram



Random Undersampling (RUS)

It is a non-intuitive method that aims to balance class distribution by randomly eliminating majority class instances in random under-sampling. 1294 majority class label labeled 0 approximates the minority class labeled 1.

Original dataset distribution: ((0: 1294, 1: 160})
Resampling dataset distribution: ((0: 160, 1: 160})

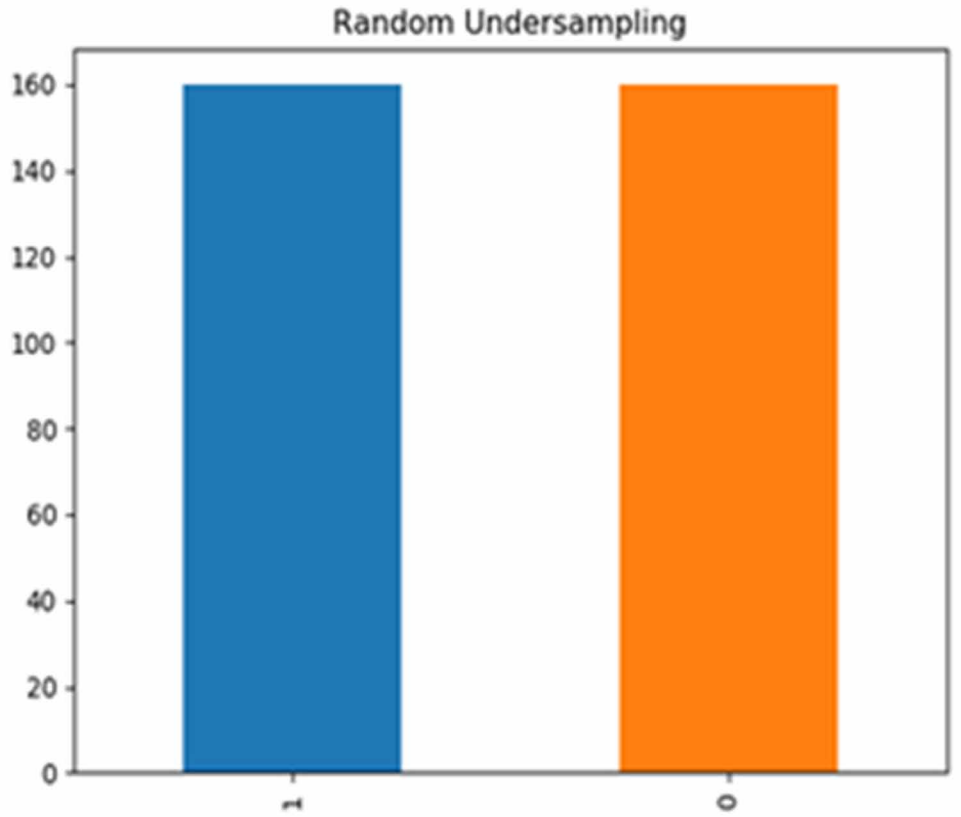
Figure 9 shows the data distribution after the majority class is approximated to the minority class.

Figure 9. Random undersampling class distribution with PCA



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Figure 10. Random undersampling class distribution histogram



Training and Test and Dataset

While making acute appendicitis disease classification, the test and training data set holdout (75/25) and the k-fold cross validation (5-fold) method of the cross-validation method were used. Data set is divided into 75% training set and 25% test set in holdut method. Classification models were trained with this training set. Model success was measured with a test data set that was previously allocated 25%. K-fold cross validation is also determined as 5-fold.

Analysis Results

In the application of the SVM algorithm, the parameter values are adjusted (parameter tuning), which gives the best classification performance. As a result of the experiments, the most ideal kernel and quality adjustment was made using the grid method. In the process of creating the SVM model, the Radial based kernel was used as the core function, the gamma value () was set to 1 and the C (cost parameter) to 1.classifier = svm.SVC(kernel='rbf', gamma=1, C=1,random_state = 0). For the SVM data set, the SMOTE algorithm is normally implemented with Random Oversamling and Random Undersampling algorithms. The tables below show Confusion Matrix tables.

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Table 5. SVM algorithm normal data confusion matrix

		Predicted Class	
		Negative (AA+)	**Positive (AA-)**
Actual Class	Negative (AA+)	TN-318	FP-0
	Positive (AA-)	FN-46	TP-0

The findings from Table 5 show that the values of TN = 318, TN = 0, FN = 46 and FP = 0. 318 patients were correctly classified and 46 patients without acute appendicitis were labeled as acute appendicitis.

Table 6. SVM algorithm SMOTE confusion matrix

		Predicted Class	
		Negative (AA+)	**Positive (AA-)**
Actual Class	Negative (AA+)	TN-204	FP-114
	Positive (AA-)	FN-16	TP-30

After using the SMOTE method that artificially reproduces the minority class from the data and makes it closer to the majority class, it is seen as TN = 204, TN = 30, FN = 16 and FP = 2 in the complexity table. The number of correctly classified patients is 234. We see that 114 patients were actually AA and 16 patients without acute appendicitis were labeled as having AA as a result of the classification.

Table 7. SVM algorithm SMOTE confusion matrix

		Predicted Class	
		Negative (AA+)	**Positive (AA-)**
Actual Class	Negative (AA+)	TN-303	FP-15
	Positive (AA-)	FN-1	TP-45

After using the Random Oversampling method, which is one of the methods that randomly selects the data from the minority class to the majority class, it is seen as TN = 303, TN = 45, FN = 1 and FP = 15 in the complexity table. The number of correctly classified patients is 348. We see that 15 patients were actually AA, but were labeled as non-AA as a result of the classification, and 1 patient was actually non-AA but as a result of the classification

Table 8. SVM algorithm RUS confusion matrix

		Predicted Class	
		Negative (AA+)	**Positive (AA-)**
Actual Class	Negative (AA+)	TN-233	FP-85
	Positive (AA-)	FN-5	TP-41

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After using the Random Undersampling method, which is one of the methods that randomly selects the data and subtracts it from the majority class and brings it closer to the minority class, it is seen as TN = 233, TN = 41, FN = 5 and FP = 85 in the complexity table. The number of correctly classified patients is 274. We see that 85 patients were actually AA and were labeled as non-AA as a result of the classification and 5 patients who were not actually AA but were labeled as AA as a result of the classification.

Table 9 provides SVM algorithm performance metrics.

Table 9. SVM Algorithm Performance Metrics

	NORMAL	SMOTE	ROS	RUS
Accuracy	0.8736	0.9313	**0.9560**	0.7527
Precision	0.5	0.6521	0.75	0.3253
Sensitivity	0.0217	0.9782	0.9782	0.8913
F-Measure	0.0416	0.7826	**0.8490**	0.4767
Kappa Value	0.0314	0.7437	0.8238	0.3578

The accuracy value is 0.87, 0.93, 0.95 and 0.75 for Normal, SMOTE, ROS, RUS, respectively. The highest accuracy values belong to ROS algorithms.

The precision value is 0.5, 0.65, 0.75 and 0.32 for Normal, SMOTE, ROS, RUS, respectively. The highest precision values belong to ROS.

The sensitivity ratio is calculated as 0.02 for normal data, 0.97 for SMOTE and ROS and 0.89 for RUS. The highest sensitivity value SMOTE belongs to ROS algorithms.

The F-Criterion ratio is 0.04 for Normal data set, 0.78 for SMOTE, 0.84 for ROS and 0.47 for RUS. The highest F-Criteria values belong to the ROS method.

The Kappa value is 0.03 for the Normal data set, 0.74 for SMOTE, 0.82 for ROS and 0.35 for RUS. The highest F-Criteria values belong to the ROS method.

Table 10. SVM algorithm k-fold 5 cross validation metrics

	NORMAL	SMOTE	ROS	RUS
Accuracy	0.8935	0.8919	**0.9651**	0.8806
Precision	0.1	0.7541	0.8590	0.7374
Sensitivity	0.0074	0.9314	0.9856	0.9295
F-Measure	0.0137	0.8086	**0.9115**	0.7946

The accuracy ratio is 0.893 for Normal, 0.8919 for SMOTE, 0.96 for ROS and 0.88 for RUS. The precision ratio is 0.1 for Normal, 0.75 for SMOTE, 0.85 for ROS and 0.73 for RUS. The sensitivity ratio is 0.007 for Normal, 0.93 for SMOTE, 0.98 for ROS and 0.92 for RUS. The F-Criterion is 0.01 for Normal, 0.80 for SMOTE, 0.91 for ROS and 0.79 for RUS. The highest accuracy and F-Criterion belongs to the ROS method.

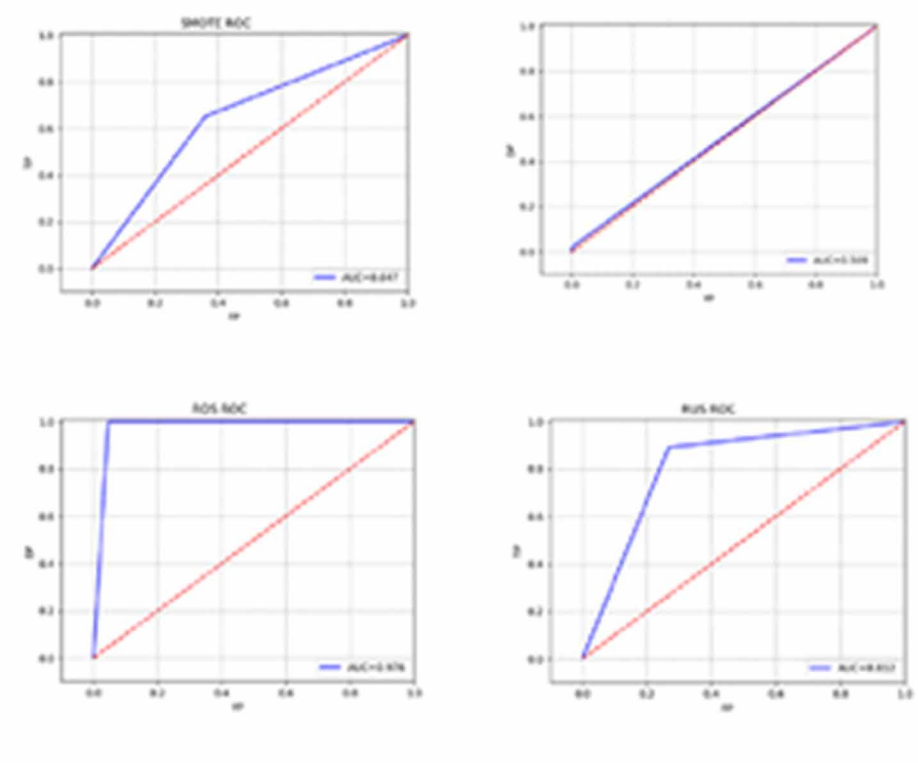
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AUC value is 0.50 for Normal data set, 0.64 for SMOTE, 0.97 for ROS and 0.81 for RUS. The ROS method shows the best performance.

Performance Metrics Measurement by Adding Age and Gender Parameters

The analysis of whether gender and age attributes not available in the Alvarado Scoring system affect the classification success by adding the values to the data. When looking at the accuracy and F-Criterion, it is seen that age and gender attributes have a performance enhancing effect on all classification algorithms. It has been observed that the SVM algorithm has achieved a high success of up to 100%. It is recommended to add age and gender parameters as attributes for all classification algorithms in the diagnosis of acute appendicitis.

Figure 11. SVM Algorithm ROC curves



After parameter tuning in the SVM algorithm, adding age and gender attributes and increasing the gamma value, the accuracy, precision, sensitivity, f-criterion and kappa value for the ROS method were determined as 100%. Decision Support System has been created for SVM algorithm and ROS method in order to show the best performance.

Figure 12 indicates the ROC Curve after adding SVM age + gender and AUC value as 1, which is the best value.

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Table 11. Metrics by adding SVM algorithm holdout age + gender attributes

	NORMAL	SMOTE	ROS	RUS
Accuracy	0.8736	0.9890	**1.0**	0.9615
Precision	0.0	0.9772	**1.0**	0.9444
Recall	0.0	0.9347	**1.0**	0.7391
F-Measure	0.0	0.9555	**1.0**	0.8292
Kappa Value	0.0	0.9492	**1.0**	0.8079

Figure 12. ROC Curve after adding SVM age + gender attributes

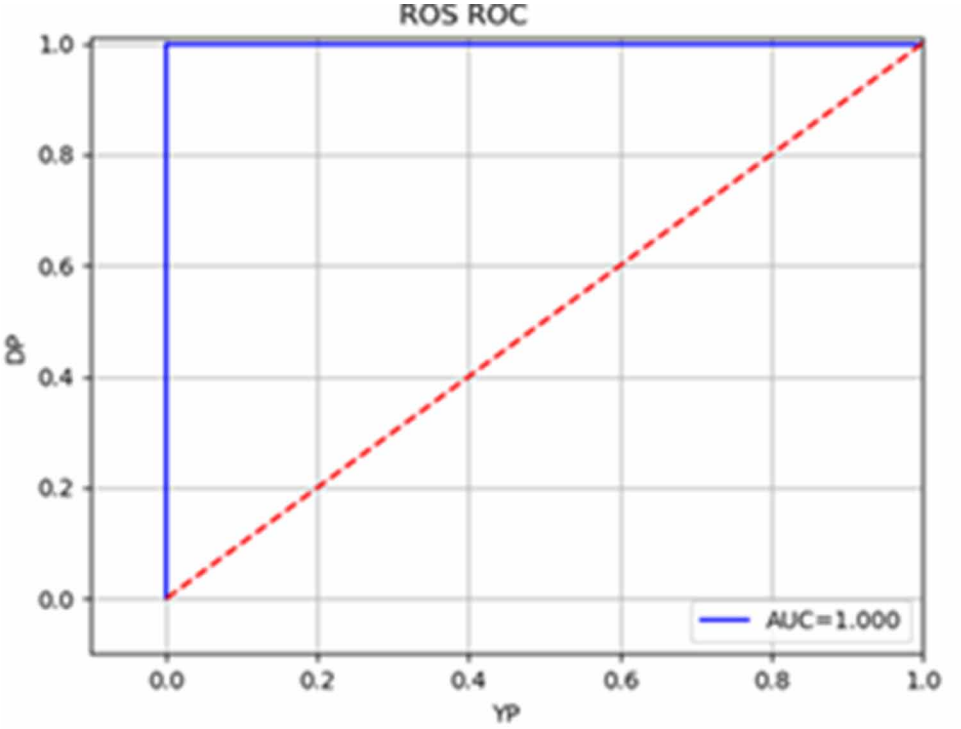


Table 12 illustrates the confusion matrix table after SVM age + gender attributes addition. The total number of correct classifications is 364, with TN = 318 and TP = 46, and achieved 100% accuracy performance.

Table 12. Confusion matrix after adding age+ gender attributes to SVM Algorithm

		Predicted Class	
		Negative (AA+)	**Positive (AA-)**
Actual Class	Negative (AA+)	318	0
	Positive (AA-)	0	46

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Decision Support System Application

Clinical Decision Support System (CDSS) is to provide clinicians with clinical information and patient-related information, to be intelligently filtered and to be presented at appropriate times to increase patient care (LaRosa, Ahmad, Feinberg, DiBrienza, & Studer, 2012).

CDSS systems are widely used in clinical care but are often ineffective due to low availability (Genes, Kim, & Thum, 2015). Human factors, usability and human computer interface principles are critical to the success of the CDSS. By evaluating the CDSS in terms of human factors, frustration and error prone conditions can be minimized to create tools designed with the user in mind. System design guidelines, such as guidelines specifically focused on designing graphical user interfaces, require better design and functional features regarding specific rules focusing on clinical usability. Evaluating the design of these interactive computer systems from a human factor engineering perspective can optimize the interaction between clinicians and the system. Eventually, it can improve both patient and clinician outcomes.

In the field of health, Artificial Neural Networks, Bayes Networks, Fuzzy Logic, Rule Based Approach algorithms are the most preferred algorithms when developing systems that provide diagnostic support. (Khoong, 1995).

As a result of the classification, a Clinical Decision Support System, which is integrated into the Python GUI interface, has been created so that the best performing Support Vector Machine algorithm will work on the infrastructure. In this application, which is especially suitable for the use of physicians, it warns Acute Appendicitis-Must be Operated or Observed, which helps him to decide when his / her qualifications are entered. The interface of the Decision Support System is presented in Figures 12 and 13.

Table 13. Performance Metrics of 5-fold after adding age+ gender attributes to SVM Algorithm

	NORMAL	SMOTE	ROS	RUS
Accuracy	0.8954	0.8128	**0.9994**	0.8328
Precision	0.0	0.9054	0.9947	0.9192
Recall	0.0	0.7757	1.0	0.7834
F-Measure	0.0	0.8159	**0.9973**	0.8329

In Figure 13, a decision support system has been created that will assist the physician and provide convenience in the diagnosis of acute appendicitis with the patient's history, physical examination and blood biochemistry parameters. The operation of the system is provided by the Support Vector Machine method, one of the data mining techniques. The patient's history and physical examination parameters such as pain migration to the right lower quadrant, tenderness in the right lower quadrant, rebound pain, anorexia, nausea/vomiting, fever, WBC Leukocytes and Netrophil Percentage (NE%) values are entered into the system. The patient's history and physical examination should be entered as 0 (absent) and 1 (present). WBC and NE% values must be entered as numerical values.

After clicking the Predict button of the values entered in Figure 14, the Must be Observed result is seen.

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Figure 13. Example of a patient with AA

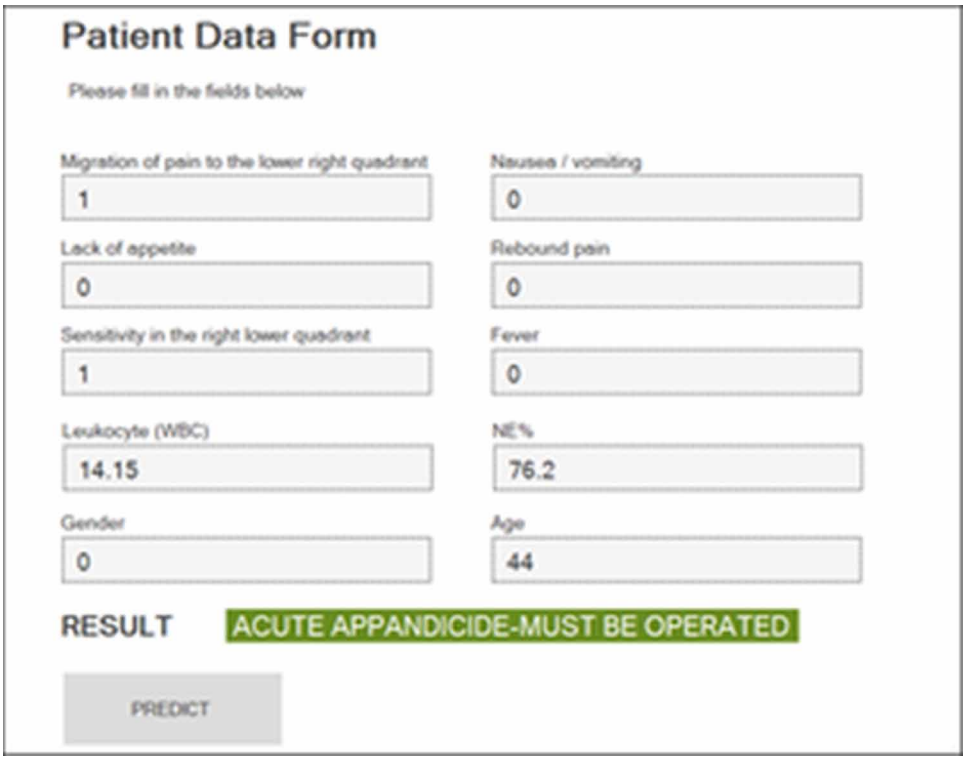
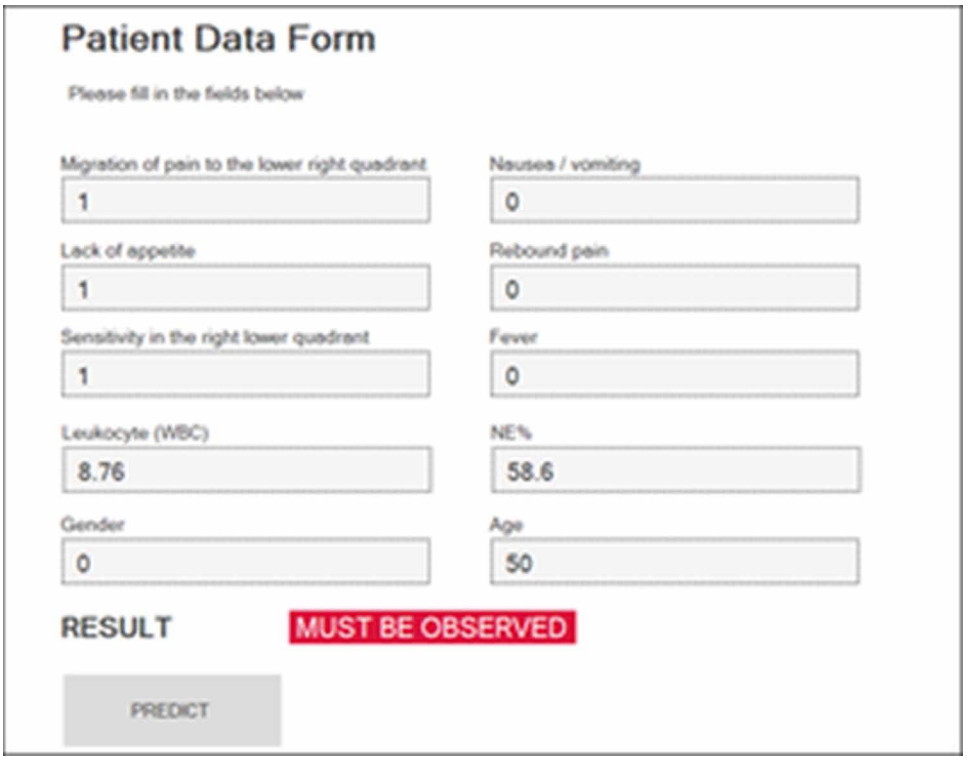


Figure 14. Example of patient without AA



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FUTURE RESEARCH DIRECTIONS

Recommended studies in the future are as follows:

- Classification algorithms can be applied by increasing the number of data. A model can be created that will be absorbed with more data and meaningful data can be produced.
- Clustering can be done to avoid dependence on the Alvarado Score.
- With the association rule, it can be determined which features of AA ones appear together.
- Different resampling methods can be used.
- Different classification algorithms can be used.
- By enabling the use of the Decision Support System by physicians, it can be investigated whether the results of the decision support system fully coincide with the decisions made by the doctor.
- Classification can be made by adding USG and BT, CRP values to the study.
- This study can then be developed in accordance with the realities of our country with new algorithms in different clinical decision-making areas that physicians need.

Data sets of AA and rare diseases consist of unbalanced data sets. The steps applied in this study constitute an example model for the classification of other diseases. First, the data should be balanced, the other measurements besides the accuracy value from the performance measurements and the properties f-criterion in this study were evaluated and evaluated.

Random Forest to support the physician and Support Vector Machines for Machine learning should support each other.

CONCLUSION

Acute appendicitis (AA) is one of the most common emergencies in patients admitted to hospital with abdominal pain in the healthcare field. In order to facilitate the clinical diagnosis of acute appendicitis, which is one of the most common emergencies in our country, and to reduce waste in health services and prevent unnecessary endangerment of human health by preventing unnecessary surgeries, specialist physicians were interviewed and this study emerged in line with their recommendations. It is very difficult to diagnose acute appendicitis. Acute abdomen, acute abdominal pain, intestinal obstructions, gastroenteritis, etc. are confused with acute appendicitis symptoms, so this study will facilitate the decision of physicians in general surgery.

In this study, which was carried out through machine learning classification algorithms for the diagnosis of acute appendicitis, an interface was created for the Support Vector Machine algorithm with 100% accuracy, which was determined to show the best performance, and a Decision Support System application was developed that can contribute to the decision-making mechanism of physicians.

The contributions of this study are listed below:

- The Alvarado Scores and Machine Learning Algorithms used for the diagnosis of Acute Appendicitis were compared and it was determined that the best classification algorithm that helps to decide whether patients presenting with abdominal pain have acute appendicitis is the Support

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Vector Machine. By adjusting the parameters and adding age and gender parameters in addition to the parameters in the Alvarado Score, 100% accuracy was found with 1454 patient data.

- The data set has been balanced by using Random undersampling (RUS), Random oversampling (ROS) and SMOTE algorithms, which are the most used methods in unbalanced data sets.
- In this study, an interface was created for the Support Vector Machine algorithm, in which the best performance was determined, and a Decision Support System application that could contribute to the decision-making mechanism of physicians was developed.
- By adding age and gender parameters, it was determined whether these two parameters are important for the diagnosis of acute appendicitis.
- Their contribution to the model is listed by looking at the coefficients of the qualities and the importance of the qualities.

In this study, a different perspective is brought to the parameters stated in Alvarado scores. Besides clinical findings, WBC, NE% changes the situation with various values in various situations. WBC and NE% were determined to depend on critical values. These values have been found to affect patients differently under certain conditions. Different values were found from Alvarado.

The findings from the accuracy and F-Criterion indicate that age and gender attributes have a performance enhancing effect on all classification algorithms. It has been observed that the SVM algorithm has achieved a high success of up to 100%. It is recommended to add age and gender parameters as attributes for all classification algorithms in the diagnosis of acute appendicitis. This study demonstrated that SVM can predict acute appendicitis with good accuracy and, can be an effective tool in clinical decision making.

As a result, this study aimed to contribute to science by determining the best predictive classification algorithm in our study, which aims to diagnose AA, which is a problem in the health sector, in the best way. It is our greatest wish that the established decision support system is used by physicians and contributes positively to human health.

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KEY TERMS AND DEFINITIONS

Acute Appendicitis: Although the function of the appendix is not known yet, researches conducted in recent years indicate that this sac functions as a shelter used by the beneficial digestive flora during disease periods.

Classification: The purpose of classification is to predict which of the pre-labeled data groups similar data belong to.

Clinical Decision Support System: These are computer programs that support physicians or other healthcare professionals in their clinical decisions. These systems are computer systems that deal with clinical data or medical information to provide decision support in a way.

Imbalanced Dataset: When much fewer instances of one class than the other class are observed in a binary-class dataset, the dataset is said to be imbalanced.

Random Over Sampling (ROS): In the random oversampling (ROS) method, the classifier is trained until the desired class ratio is reached, while it is used to balance the class distribution by randomly multiplying the minority class label samples to approximate the number of class labels.

Random Under Sampling (RUS): It balances class distribution by randomly eliminating majority class instances in random under-sampling.

SMOTE (Synthetic Minority Oversampling Technique): Each minority class sample is taken and synthetic samples are created by looking at any or all of the k neighbors of this sample. Thus, the minority class is over-sampled.

Support Vector Machine (SVM): SVM has been used to solve problems related to regression and classification.

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Chapter 11
Detection of Diabetic Retinopathy (DR) Using Convolutional Neural Network (CNN) and Multiple Classifier Techniques in Machine Learning

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ABSTRACT

The medical industry has advanced in a manner where high end technologies are used for early detection and analysis of diseases that are hard to encounter with normal procedures of the medical field. One such disease is diabetic retinopathy (DR) further classified as non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR) conditions. Early detection of NPDR is a challenging task, and it requires examination of fundus images in an amplified manner. To overcome these early detection of DR, the authors propose an automated system that will be using machine learning classifier techniques with combination of convolutional neural network (CNN) to self-train the system and detect the early stages of retinal scans by feature extraction and use of existing retinal scan databases. Hence, the system will eliminate the human flaw of inability to detect early DR in diagnosis and will help us treat the patient in early stages.

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INTRODUCTION

In this progressive world now day's diabetes has become a common disease that is affecting most of the world population. With diabetes many medical conditions are getting encountered that includes diabetic retinopathy which is mainly concerned with damage to retina that can cause vision loss. Detection of such diabetic eye in modern world can be achieved with help of machine learning techniques that include neural network, computer aided programs. In such systems fundus images are provided to the neural deep learning algorithms to extract features in the fundus images and then calculate the diabetic eye condition. Such mechanism helps us detect the conditions in fundus images more accurately and efficiently. Diabetic retinopathy has mainly 2 types that are to be detected for retinal diseases like Non-Proliferative Diabetic Retinopathy disease(NPDR) and Proliferative Diabetic Retinopathy disease(PDR)(Wang et al., 2020).Medical industry nowadays has advanced in a manner where high end technologies are used for early detection and analysis of diseases that are hard to encounter with normal procedure of medical field. One of such disease is Diabetic retinopathy(DR) further classifield as Non-Proliferative Diabetic Retinopathy (NPDR) disease and Proliferative Diabetic Retinopathy disease(PDR) conditions which are caused by diabetes. Early detection of NPDR is a challenging task and it requires examination of fundus images in a amplified manner. To overcome these early detection of DR we are proposing a automated system that will be using machine learning classifier techniques with combination of convolutional neural network(CNN) (Alves, 2020) to self train the system on its own and detect the early stages of retinal scans by feature extraction and use of existing retinal scan databases. Hence the system will eliminate the human flaw of inability to detect early DR in diagnosis and will help us treat the patient in early stages itself. CLAHE method will be used for preprocessing of fundus images which will be used by CNN. CNN will extract features from the input set of fundus images and pass it to classifiers where the accurate result will be obtained to detect the DR. Medical industry nowadays has advanced in a manner where high end technologies are used for early detection and analysis of diseases that are hard to encounter with normal procedure of medical field. One of such disease is Diabetic retinopathy(DR) further classified as Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy(PDR) conditions which are caused by diabetes. Early detection of NPDR is a challenging task and it requires examination of fundus images in a amplified manner. To overcome these early detection of DR we are proposing a automated system that will be using machine learning classifier techniques with combination of convolutional neural network(CNN) to self train the system on its own and detect the early stages of retinal scans by feature extraction and use of existing retinal scan databases. Hence the system will eliminate the human flaw of inability to detect early DR in diagnosis and will help us treat the patient in early stages itself. CLAHE (Lands et al., 2020) method will be used for preprocessing of fundus images which will be used by CNN. CNN will extract features from the input set of fundus images and pass it to classifiers where the accurate result will be obtained to detect the DR.

BACKGROUND

Detection of Diabetic Retinopathy (DR) is mainly concerned with detection of early damage caused by diabetes to the eye of the patient that can be achieved by help of machine learning techniques that are using mathematical computation and extraction techniques to classify the input retina optical coherence tomography(OCT) into specific conditions to determine stages of Diabetic Retinopathy(DR). Early stage

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non-proliferative Diabetic retinopathy disease (NPDR) or proliferative Diabetic retinopathy disease (PDR) makes use of convolutional unsupervised neural network(CNN)(Ghazal et al., 2020) to extract features from the fundus images. It uses support vector method(SVM) as classifier. Many CNN are trained on basis of divisons(Alves, 2020) that are nothing but predefined datasets that are to be used to detect features of DR. Random forest, k-neighbor classifier, denseforest(Reddy, 2020) are some of the techniques that are recently used for diabetic eye condition. These different classifiers are ensemble into a machine learning system to classify features extracted by neural networks. Fundus images are the images of eye taken from different perspectives that play an important role to help system detect Diabetic eye diseases (DED)(Sarki et al., 2020).Different perspectives are predefined into this system for detecting DED and based on that conditions only DED are predicted. Many researchers have created systems that detect diabetic eye but very few focus on how severe the disease is or at what stage the disease is. This research has created a matrix(Lands et al., 2020) of the findings of the eye images and classified it on basis of five different categories. Microaneurysms(Usman & Almejalli, 2020) are nothing but small blood clots that occur in diabetic fundus images of eye. Feature-set tuning is one of the technique that uses genetic programming(Usman & Almejalli, 2020) and set of 28 features to classify the fundus images. Genetic programming mainly involves mathematical expression calculation which helps us achieve accuracy in feature extraction and evaluation. Diabetic eye detection and feature extraction is one of the key point in simultaneous diagnosis of Diabetic eye diseases through deep learning(Wang et al., 2020). It includes hierarchical multi-task neural network(Wang et al., 2020) to do two different tasks like feature extraction and detection differently. Creating and 3D Multi-path Convolutional Neural Network Based(Eladawi, 2019) in an system is indeed helpful for detection of Diabetic Retinopathy(DR) through computer aided systems. It includes consideration and segmentation of fundus images to have deeper understanding and detection of DR. Microaneurysms detection with lesion algorithm(Qiao et al., 2020) of neural network in detection of non-proliferative Diabetic retinopathy NPDR helps achieve accuracy and consistency. Adaptive Histogram Equalization with preprocessing technique like CLAHE method(Momeni Pour et al., 2020) helps us get a amplified view of blood vessels that are to be used for feature extraction and detection of diabetic eye diseases. Thus making it more easier to function for neural networks.

MAIN FOCUS OF THE CHAPTER

Development of an automated self-learning system that can early detect non proliferative Diabetic disease in retinopathy NPDR or proliferative Diabetic disease in retinopathy PDR in an efficient manner without any human intervention. Tracing of DR is a complex crutial process that occurs in diabetic patients which remains undetected and can cause severe problems. Hence to overcome that and detect it in early phase we need such kind of system that can help us with accurate detection. This will be achieved by EfficientNetB5 CNN model and classifier techniques.

Issues, Controversies, Problems

Diabetic Retinopathy (DR) is one of the diabetic diseases that involves early detection which is sometimes not achieved by human computation in that case there needs to be a system that can automatically check for fewer symptoms and guide us with DR to the patients. Hence this will help patients with early treatment .So development needs to be done in machine learning which can take help of different

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Table 1.

Sr.No	Paper	Research Gap
1	"M. Ghazal, S. S. Ali, A. H. Mahmoud, A. M. Shalaby and A. El-Baz, "Accurate Detection of Non-Proliferative Diabetic Retinopathy in Optical Coherence Tomography Images Using Convolutional Neural Networks," in IEEE Access, vol. 8, pp. 34387-34397, 2020, doi: 10.1109/ACCESS.2020.2974158."	SVM was the only classifier technique used. Use of other classifiers like Kmean-Star, Kmean -Nearest Neighbor (kNN), Random Forest, and Random classifiers of tree structure were also suggested to achieve better results.
2	"S. S. A. Alves et al., "A New Strategy for the Detection of Diabetic Retinopathy using a Smartphone App and Machine Learning Methods Embedded on Cloud Computer," 2020 IEEE 33rd International Symposium on Computer-Based Medical Systems (CBMS), Rochester, MN, USA, 2020, pp. 542-545, doi: 10.1109/CBMS49503.2020.00108."	Only 3 predefined Diavision sets were used for training the CNN which can be increased to multiple sets of Diavision for future implementation was proposed.
3	"G. T. Reddy et al., "An Ensemble based Machine Learning model for Diabetic Retinopathy Classification," 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE), Vellore, India, 2020, pp. 1-6, doi: 10.1109/ic-ETITE47903.2020.235."	Limited size datasets were used. Instead it can comprise of larger size datasets with multiple type on data like images and geospatial data as future implementation.
4	"R. Sarki, K. Ahmed, H. Wang and Y. Zhang, "Automatic Detection of Diabetic Eye Disease Through Deep Learning Using Fundus Images: A Survey," in IEEE Access, vol. 8, pp. 151133-151149, 2020, doi: 10.1109/ACCESS.2020.3015258."	Review and result analysis was not carried onto exhaustive keywords but only particular keywords.
5	"A. Lands, A. J. Kottarathil, A. Biju, E. M. Jacob and S. Thomas, "Implementation of deep learning based algorithms for diabetic retinopathy classification from fundus images," 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI)(48184), Tirunelveli, India, 2020, pp. 1028-1032,doi: 10.1109/ICOEI48184.2020.9142878."	1.Some supervised intervention was needed to gain DR more efficiently. 2.Use of pseudo labeling for semi-supervised system was proposed as well.
6	"I. Usman and K. A. Almejalli, "Intelligent Automated Detection of Microaneurysms in Fundus Images Using Feature-Set Tuning," in IEEE Access, vol. 8, pp. 65187-65196, 2020, doi: 10.1109/ACCESS.2020.2985543."	Ramifications of the current investigation on clinical applications is yet to be finished.
7	"J. Wang, Y. Bai and B. Xia, "Simultaneous Diagnosis of Severity and Features of Diabetic Retinopathy in Fundus Photography Using Deep Learning," in IEEE Journal of Biomedical and Health Informatics, doi: 10.1109/JBHI.2020.3012547."	NPDR, new vessels somewhere else (NVE), new vessels at the disc(NVD), preretinal fibrous proliferation(PFP), glassy or preretinal discharge (VPH), and foothold retinal separation (TRD) were consolidated in dataset which can cause sway on Average exactness value(AP). Investigation of that variety in dataset sway on outcomes was not broadly broke down.
8	"N. Eladawi et al., "Diabetic Retinopathy Grading Using 3D Multi-path Convolutional Neural Network Based on Fusing Features from OCTA Scans, Demographic, and Clinical Biomarkers," 2019 IEEE International Conference on Imaging Systems and Techniques (IST), Abu Dhabi, United Arab Emirates, 2019, pp. 1-6, doi: 10.1109/IST48021.2019.9010210."	System was unable to detect non-proliferative Diabetic retinopathy disease(NPDR) and proliferative Diabetic retinopathy disease(PDR) in early stages.
9	"L. Qiao, Y. Zhu and H. Zhou, "Diabetic Retinopathy Detection Using Prognosis of Microaneurysm and Early Diagnosis System for Non-Proliferative Diabetic Retinopathy Based on Deep Learning Algorithms," in IEEE Access, vol. 8, pp. 104292-104302, 2020, doi: 10.1109/ACCESS.2020.2993937."	System lacked training on non-Microaneurysms (MAs) that would have helped differentiate between healthy and diabetic eye.
10	"A. Momeni Pour, H. Seyedarabi, S. H. AbbasiJahromi and A. Javadzadeh, "Automatic Detection and Monitoring of Diabetic Retinopathy Using Efficient Convolutional Neural Networks and Contrast Limited Adaptive Histogram Equalization," in IEEE Access, vol. 8, pp. 136668-136673, 2020, doi: 10.1109/ACCESS.2020.3005044."	Implementation of efficient B5 network for better classification as future work.

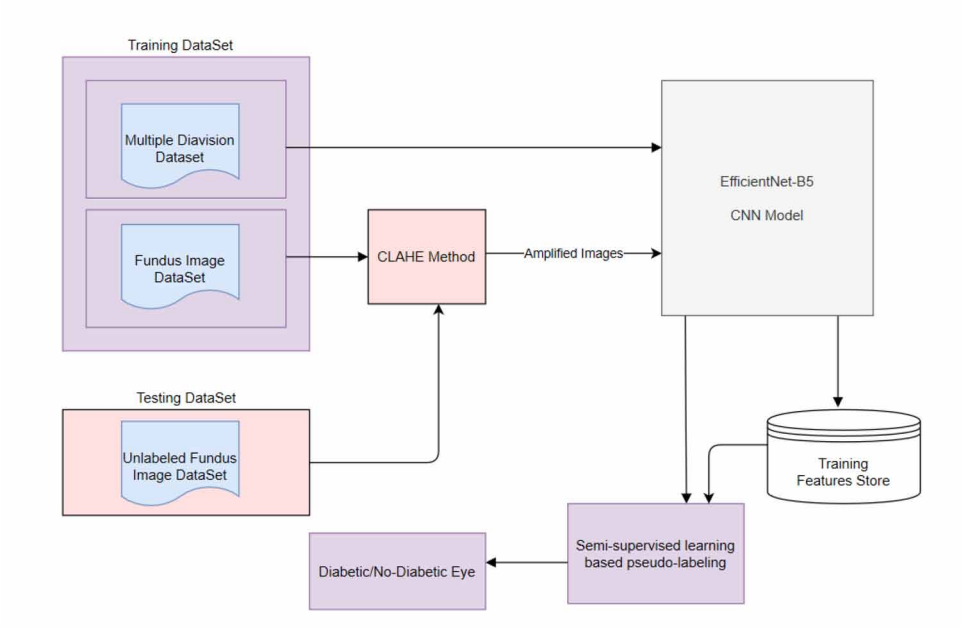
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algorithms for easy and accurate computation of diseases. If we have multiple types of datasets with the preprocessing refinement of data as a feature, then the automated system will train itself in an efficient manner. But if it is not trained onto refined dataset then the system may differ in its output in respect of accuracy and efficiency in detection of diabetic eye. If we have multiple types of datasets with the preprocessing refinement of data as a feature, then the automated system will train itself in an efficient manner. But if it is not trained onto refined dataset then the system may differ in its output in respect of accuracy and efficiency in detection of diabetic eye.

SOLUTIONS AND RECOMMENDATIONS

System mainly concentrates on training of EfficientNet-B5 CNN model on basis of the preprocessed data that is being provided to it in form of fundus images that are amplified with help of CLAHE method. Further the features extracted are provided to classifiers for the classification of different feature according to the similarity and labeling and stored into database.

Figure 1. Architecture Diagram



Following are the modules that will be implemented in the system.

1. Diavision creation: Diavision creation mainly involves analysis and listing of different features that are mainly encountered in fundus images regarding the Diabetic eye diseases. They are written in a programmatic way that is readable to computerized system for automatic analysis.These are methods of data collection:-

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a. Diavisions:- They are nothing but set of features and findings that are given to automatic system to detect specific type of problem.
b. Fundus images:- Actual data in form of optical images of healthy and diabetic eye will be taken from a medical labs across the city.

2. Pre-Processing CLAHE method: Preprocessing stage utilizes CLAHE strategy which includes enhancement of every single segment of fundus picture that is given to it. It gives us an explained perspective on every single nerve around there. In CLAHE, the distinction improvement close by a given pixel regard is given by the slope of the change work. This is relating to the grade of the local total scattering work (CDF) and thusly to the assessment of the histogram at that pixel regard. CLAHE limits the escalation by cutting the histogram at a predefined regard before preparing the CDF. This limits the grade of the CDF and likewise of the change work. The motivating force at which the histogram is cut, the supposed catch limit, depends upon the normalization of the histogram and in this manner on the size of the neighborhood. Fundamental characteristics limit the resulting heightening to some place in the scope of 3 and 4. It is beneficial not to discard the piece of the histogram that outperforms beyond what many would consider possible yet to redistribute it comparatively among all histogram compartments.
3. Semi-Regulated network creation and feature extraction: This module includes preparing of EfficientNet-B5 CNN model on premise of the preprocessed information that is being given to it in type of fundus pictures that are enhanced with assistance of CLAHE strategy. EfficientNet-B5 CNN performs include extraction and division of the pictures and furnishes a 3D perspective on pictures with its highlights. In a CNN, the data is a tensor with shape (number of pictures) x (picture height) x (picture width) x (input channels). In the wake of going through a convolutional layer, the image gets detached to a segment map, with shape (number of pictures) x (feature map height) x (incorporate guide width) x (incorporate guide channels). A convolutional layer inside a neural association should have the going with credits:

Convolutional channels/pieces described by a width and height (hyper-limits). The amount of data channels and yield channels (hyper-limit). The significance of the convolution piece/channel (the data channels) should move toward the number channels (significance) of the data feature map. The hyper-parameters of the convolution movement, like padding size and step. Convolutional layers convolve the data and pass its result to the accompanying layer. This resembles the response of a neuron in the visual cortex to a specific stimulus. Each convolutional neuron estimates data only for its open field. Though totally related feedforward neural associations can be used to learn incorporates and request data, this plan is unworkable for pictures. It would require a high number of neurons, even in a shallow plan, in light of the amazingly colossal information sizes related with pictures, where each pixel is an appropriate variable. For instance, a totally related layer for a (bit) image of size 100 x 100 has 10,000 burdens for each neuron in the resulting layer. Taking everything into account, convolution diminishes the amount of free limits, allowing the association to be deeper. For occurrence, paying little notice to picture size, tiling 5 x 5 region, each with comparative shared burdens, requires only 25 learnable limits. Using regularized loads over less limits avoids the vanishing tendency and exploding incline issues seen during backpropagation in customary neural organizations. The convolutional layer is the middle construction square of a CNN. The layer's limits involve a lot of learnable channels (or parts), which have a little open field, yet connect through the full significance of the data volume. During the forward pass, each channel is convolved across the width and height of the data volume, calculating the spot thing between

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the channel areas and the data, conveying a 2-dimensional incitation guide of that channel. Accordingly, the association learns channels that start when it perceives some specific sort of feature at some spatial circumstance in the information.

Stacking the activation maps for all channels along the significance estimation outlines the full yield volume of the convolution layer. Every section in the yield volume can thusly be unraveled as a yield of a neuron that looks at a little region in the data and offers limits with neurons in a comparative incitation map.

4. Classifier Implementation using pseudo-labeling: Pseudo labeling is done by training the pseudo classifier onto a predefined set of labels that we encounter while differentiating the diabetic eye diseases. Once the pseudo classifier trains itself it is capable of labeling and classifying the data input that it receives from EfficientNet-B5 model. Hence the classifier labels the fundus images into labeled clusters. pseudo-naming technique utilizes a little arrangement of named information alongside a lot of unlabeled information to improve a model's presentation. The actual procedure is inconceivably basic and follows only 4 fundamental advances:
   Train model on a bunch of named information
   Utilize the prepared model to anticipate names on a clump of unlabeled information
   Utilize the anticipated names to figure the misfortune on unlabeled information

With such a lot of headway in innovation and processing power, we are quiet in managing large numbers of the directed learning issues. This learning strategy requires huge loads of named information and we train our model on this information again and again to get familiar with the example. This is compelling and very performant. Be that as it may, we will not have the advantage of named information consistently. In some ongoing cases, we will consistently have unlabeled information and need bunches of time and exertion to mark this physically. We have semi-directed learning(SSL) techniques to counter the unlabeled information. It is a methodology that joins a modest quantity of marked information and a lot of unlabeled information during preparing. It improves the model's power also. Pseudo naming is one such SSL approach that assists with managing unlabeled information. From the outset, we can explain a little bunch of information and train a model with it and afterward utilize that model to identify objects on the unlabeled information, The marks clarified by the model is called pseudo names. We would then be able to consolidate both marked and pseudo named information and train the model once more. We would pseudo be able to name all the unlabeled information without a moment's delay or we can do it in bunches as well.

5. Result analysis and evaluation: Result investigation and assessment incorporates computation of exactness, review, F-measure and accuracy. In design affirmation, information recuperation and portrayal (AI), precision (furthermore called positive insightful worth) is the little piece of critical events among the recuperated cases, while audit (in any case called affectability) is the immaterial bit of appropriate events that were recuperated.
   a. **Accuracy:** Accuracy is closeness of the estimations to a particular worth.

$$Accuracy = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} \tag{1}$$

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b. **F-measure**: **F**1 **score** is a measure of a test's accuracy. It is calculated from the precision and recall of the test.

$$f-measure = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (2)$$

Following are few of the objectives that will be fulfilled by research:-

i. To train the system on basis of multiple divisions and amplified images simultaneously for feature extraction to improve accuracy.
ii. To implement EfficientNet-B5 technique for classification of amplified images for uniform scaling to enhance efficiency.
iii. To develop the system to detect early non-proliferative Diabetic retinopathy (NPDR) & proliferative Diabetic retinopathy (PDR) by integrating different types of datasets to improve average precision value.
iv. To implement pseudo labeling semi-regulated learning classifier for optimization of proposed system.

FUTURE RESEARCH DIRECTIONS

Implementation of multiple classifier technique to analyse the results obtained through the solution recommended . Results can be classified to obtain more accurate results will be on used.

CONCLUSION

Accurate results that will help remove the early detection flaws caused by human intervention while studying the fundus images of patient. Hence early detection will help find the Diabetic eye to get appropriate treatment.

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Chapter 12
Face Detection With Face Mask for COVID-19 Pandemic Using Neural Networks

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ABSTRACT

The COVID-19 virus can be spread through contact and contaminated surfaces; therefore, typical biometric systems like password and fingerprint are unsafe. Face recognition solutions are safer without any need of touching any device. During the COVID-19 situation as all of the people are advised to wear masks on their faces, the existing face detection technique is not able to identify the person with face occlusion. The fraudsters and thieves take advantage of this scenario and misuse the face mask, favoring them to be able to steal and commit various crimes without being identified. Face recognition methods fail to detect or recognize the face as half of the face is masked and the features are suppressed. Face recognition requires the visibility of major facial features for face normalization, orientation correction, and recognition. Thus, the chapter focuses on the facial recognition based on the feature points surrounding the eye region rather than taking the whole face as a parameter.

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I. INTRODUCTION

The COVID-19 has resulted in a huge number of security concerns as well as causalities. This pandemic has hugely affected the lives of almost all the people in the world. In order to reduce the spread of coronavirus, people are advised to wear N95 masks to protect themselves from any airborne microbes. Thus the face recognition becomes a challenging task since the facial features are hidden and unreportable. A primary focus of our paper is to come up with suggestions and probable algorithms for dealing with these above mentioned problems in a fast and efficient manner.

Face recognition methods fails to detect or recognize the face as half of the face is masked and the features are suppressed. Face recognition requires the visibility of major facial features for face normalization, orientation correction, and recognition. The nose is one such facial feature which is covered by masks causing hindrance to traditional methods of achieving this goal. Although a remarkable number of new ways have already been developed which are very efficient, there is still a concern that developing such solutions is becoming much more difficult by the day. With the current algorithm, the masked face detection, helpful for video surveillance is not possible. Main concern is that even after the circulation of Covid-19 vaccines such issues will always exist as flu and other contagious diseases that spread through air will always exist. Especially in the tropical region and in the Asian countries this issues is far dominant. With increasing population and depleting resources the standard of living has degraded considerably. Due to this the crime rates have almost doubled. Now due to the masks covering the major part of faces, the notoriety of such criminals has also gone up due to the lack of efficient enough surveillance capabilities. The main focus of this paper is to study and develop such a model that would reduce crimes.

II. RELATED WORK

Image recognition could be a very good example of the real life application of the concepts of machine learning and deep learning. The reason behind this can be easily understood by looking at the basic steps required for such applications. The base procedure of image matching involves some standard steps such as image acquisition, using various transforms and classifying the information extracted from these images, training models and testing the efficiency and accuracy of the model developed. But with the recent developments within the fields of machine learning and data structures, it is more beneficial to use 3D images or models of face to accomplish our task since because of the Mask most of the info points are already out of reach. Engineers from Nanyang Technological University, Singapore have come up with a good method to try and do so using Point signature. Generally a face recognition problem is treated as a 3D recognition problem of rigid surface, and it is assumed that the structure of this 3D rigid surface does not change significantly. But this is not the case as with different orientation of face and with various emotions displayed by the face, this 3D structure changes form significantly and hence it is advised to treat the problem of face recognition as a 3D recognition problem but with a non-rigid surface.

Now, working with a pattern that cannot have a rigid form is pretty difficult and hence landmarks such as facial features must be used to add constraints to the possible range of changes that can occur in this non-rigid surface called face. This addition of constraints will automatically convert the problem of 3D recognition of non-rigid structure to a semi-rigid structure. Regions, like nose, eyes, etc., can be used as these landmarks (Han et al.,). Using this logic the authors are able to use various open source Tools that are compatible with the platform of option to identify, read and store the pictures as a 3D

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model subjecting to those particular features which can make it easier to store in addition as Easier to access and process. Now the authors are developing this paper for security purposes and for such applications, having a Still image is bit tedious instead making this model for a moving face would be more sensible as one can use surveillance cameras and CCTV's for this application(Chen et al., n.d.). Some engineers from the University Sriwijaya Palembang, Indonesia propose a template processing technique that minimizes the area under consideration by eliminating the unnecessary regions and only working with the features in ROI (Region of Interest). The regions that would be included as the region of interest would be the parts of eyes, nose, lips, chin, forehead, etc. The researchers also proposed a way to avoid any potential matching errors due to the different orientations of the features by training the model by rotating the images which will cause the model to also learn the features in different orientation. The Processor should then detect the angle of the face and store it to as usable information. For This process it's assumed that the environment may be a controlled environment with stable lighting.

Now we also need to recognize the natural features of a human face to match it or recognize it. And for this task, Mr. Ruiyang Sun, Faculty of mathematics, University of Waterloo, Canada has a proposed a statistic approach. As per him, in order to analyse the natural feature matching methods in deep learning models, the natural classifiers should be taken a look at. The conventional method of doing so is to find local groups of features, group them together to form a pool of information and store it in terms of statistical parameters or tables and datasets that can be used as a unique identity for that image. Now, such tables of features are further compared with other tables which represent other unique images and based on statistical operations and analysis, we find the differences in these two unique sets of features. Now these differences or mismatches of features that occur during this difference finding, can be termed as the errors. And the difference of 100 and the ratio of the number of this errors to the total number of features extracted from an individual image would give us the accuracy of the model. This kind of implementation is essentially done with images first converted into gray scale so as to avoid any unnecessary computations as gray scale images are entirely sufficient in providing key features of an image. Natural feature matching of world scenes refers to identifying the unique objects or faces in an image with vast number of objects in the background which cause a hindrance to the matching process. Our brain does this task all the time and our brain is so proficient in this task that it is seamless but for a machine algorithm such as task would be very difficult mainly because of the inefficiency of image recording devices which cause an inconsistency in the recorded pixel values of the same object, different angles of the object in different images and pixel wise matching process which takes a lot of machine time (Chakraborty, 2018).

Now comparing and storing each pixel is very time consuming and hence some engineers from Simon Fraser University, Vancouver, B.C., Canada has proposed the use of probabilistic feature matching technique. Similarity-based methods or models which does the tasks of image recognition and matching based on the similarity observed among the images are very efficient. Naturally to determine whether two objects are similar we verify the similarities of the two. Any two thing, object, people or image would be deemed similar if and only if the features or characteristics of the two match (Wang et al., n.d.). In their approach, the similarity between two images is defined as the inner product the actual similarities found in the image and the probable matchings which are learned by optimizing a best matching loss function. Intuitively, a Feature matching probability function would essentially be used to display how well the two features match (Wang et al., n.d.). This type of mathematical probabilistic approach could be very useful for our project since lack of information is a major road block that we will face and hence having mathematical quadratic equations that could predict or give the probability of the value of an unknown pixel would help in the cause.

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Some of the paper referred discussed on the GAN method of face detection where a two layers of GAN are used (Yan et al., n.d.). GAN is popularly known for generating the realistic faces of the person even if the person does not exist. Here a two layers of GAN is used, one for the reconstruction of the face and the next layer is for generating the more realistic face.

The task of identifying a person inside a face mask starts with the task of classifying whether the person is wearing a face mask or not. The detection of a face mask in itself is summation of two tasks namely, detection and classification. This is because one first needs to locate a face, read it and analyze whether the face located has a mask on or not. The task of locating the face is the most crucial task of all as face localization is the pre-requisite to all types of face detection techniques. The researchers have been working on developing a method to localize face with least possible readable face data. The reasons earlier to the pandemic was the advancement of photography field and the face detection applications. The camera systems failed to recognize a face as they could not localize the face in less number of frames and hence to increase picture quality and face detectability. And hence techniques such as RetinaFace face detector, RetinaFace AntiCov model, one-shot learning face-detection model, etc. were developed. The majority of these models work on the principal of detecting the significant landmarks of the face (Deng et al., 2020). One shot learning is a special exception where the input image is singular for the complete training phase. The one short learning model in a Siamese network works with three images. One anchor image which is a reference image, one positive image which is an image of the same person and one negative image which is an image of a different person. Each image is passed through a pre-trained neural network which have same weights for all three images and we receive unique embedding form each image. Now we have three sets of embeddings and we compare these three sets of embeddings using a special loss function called triplet loss function. Triplet loss is basically the difference of the Euclidian distance of the features of anchor and positive image and the features of anchor and negative images. Now, we update the weights of the neural network model used in order to minimize this loss function (Koch et al., 2015).

Now using the information and work mentioned above we have solved the problem of face localization but the task that arises now is the problem of how will the system determined that the identified face which is having a region of face covered is masked or not. A person can be having his/her hand on the face at the moment of when the image is taken. Also as we have observed around us, people prefer keeping the masks on chin and such cases should be counted as the face mask is not present. Hence researchers from University of Ljubljana have given a solution that RetinaNet can be used to develop a one shot learning model to classify whether the mask is worn properly or not (Batagelj et al., 2021). This approach is highly useful for our scope as well.

III. METHODOLOGY

The objective for the scope of this project is to detect a human face in the video input, analyzing whether the person is wearing a mask or not, if wearing determine whether this person exists in the database or not. To achieve these goals, the proposed system is divided into two parts: - A) to develop a system to be able to differentiate between the person with and without the face mask. This is much of a primary step to detect the person with a mask. Upon being able to distinguish between the parameters, the next step is B) to recognize the person with the mask with the available feature, so as to avoid inconvenience related to the existing algorithms offer. The person to be recognized is to already exist in the dataset,

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further on training of these dataset the system is expected to recognize the person with and without a mask. Figure1 explains the flow of the system. Where in figure 1, the block Video: - A live video is fed to the system to detect face in real time. Pre-processing:- The training of system to differentiate the faces. Mask detection: -Upon training system is capable to detect the mask. Data generation: - The data of the person to be detected must be present in system. Feature Extraction: - The visible feature is to be extracted using the proposed algorithm. Matching: -At the stage the features are compared with that of the dataset at the minimum difference is considered. Further on the proposed system is to be implemented on GUI as well to make the experience more user friendly.

IV. APPROACH

As the paper focus on detecting the person with face mask on. The primary step is to filter out the feature of the face and store it for further processes. So the primary step is to classify the faces as masked or unmasked in real time, followed by localizing the mask region. For getting this done, we apply cropping filter and are only left with the Region of Interest. Next, this ROI is described using features extracted using deep learning models. Each face feature need to be extracted and stored in distinctly separated dictionaries or tables in order to make a database for further studying and determining the distinct patterns. Some recent advancements in the field of image matching has suggested an approach of using supervised learning to retrieve the information of the missing parts of image (Chakraborty, 2018). Despite being theoretically useful, in real life applications, such approaches would prove to be highly time consuming and difficult to implement. And despite the recent advancements in the fields of deep learning and machine learning, the standard frameworks for pattern recognition still need to perform a ton of calculations of countless parameters of various layers. This by default increases the hardware specifications required of the machine used for the implementation (Wang et al., n.d.).

The easiest way to deal with such problems is to represent the image as a set of local features which are shuffled randomly. Each of these features will represent a distinct section from the image. Now, all these features are passed to a pattern identification algorithm and the extracted pattern of features would be stored and used to classify the images as recognized or not. Now this approach of encoding the image sections into useable numeric values termed as features has many advantages. First and foremost is the fact that it is a light-weight implementation of a real world problem. There is also the demerit of having information cells of different dimensions as the face covers different area of the face. Thus, the authors wait for the masked face to be detected properly and thereafter the snap of the masked face is to be recorded as it is easier to work on image than video. This image is then stored in the same file as that of the code. The stored image then undergoes the series of operation to extract the feature useful for reorganization.

Figure 1. Flow chart of the proposed system



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Figure 2. Unmasked and Masked face Detection



As the primary objective to detect the face mask irrespective of the facial orientation is fulfilled, so the authors proceed with the next step that is to recognize the face by highlighting the correct name. Now feature extraction from the image using various filters is commenced in order to match t with the feature set of other images to classify as matched or not. For this the authors used a use traditional brute force matcher which is easy to implement. Brute force matcher works on the principle of KNN machine learning models. It being a simple and easy to implement algorithm is also highly efficient. It is a basic algorithm that calculates the hamming distances between reference points to determine the similarities. And the closest one is returned. Matcher returns only those match with value of the two features in both sets should match each other. It gives consistent result, and act as alternative for ratio test.

For the task of feature extraction the authors used ORB and SIFT toolboxes which are an open source library of python. The features are nothing but the corners or high contrast regions of the image which are stored and analyzed using various algorithms to conclude the similarity between two objects. Similar to humans. Humans unconsciously store the special or key features of things they see, they can also say that we store the corners or distinct appearances of objects or faces that they see and when it comes to recognition, the brain efficiently retracts those stored key features and on the basis of years of training that one passes their brains through, one can conclude that the object in question is recognized or not. In similar fashion the aim of authors for using such basic algorithms was to mimic the algorithm used by human mind and follow the steps taken by it.

SIFT stands for Scale Invariant Feature Transform and it is a feature extractor which has proven its worth in various object detection applications, however when it comes to real-time implementations, the SIFT showcases some major drawbacks. First and foremost being its computational complexity. SIFT algorithm is divided in 4 tasks. (i) Finding the scale-space extremes of the image. Taylor series expansion is by default used by SIFT to increase the accuracy of extrema location, (ii) Determine the key points and elimination of points that show low contrast which is not preferred for such applications, this is simply done by applying a threshold values to the extracted contrast points. Typically a contrast of less than 0.03 is rejected by the algorithm. By doing this we achieve strong interest points for the application, (iii) Based on the local gradient, an orientation is assigned to the key point and (iv) A descriptor is generated to define this particular key point, its magnitude and orientation. For this a 16x16 neighborhood around the detected key point is taken and further divided into sub blocks of 4x4(Karami, 2015).

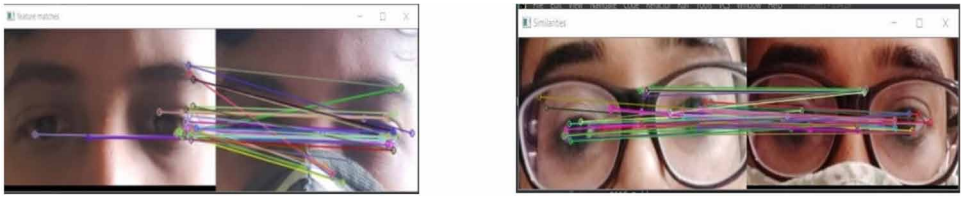
For real-time applications, it is highly expected from the model to be agile and cost effective so that the run time can be reduced, this is not always achievable from a computational cost inefficient algorithm such as SIFT. Hence came the need to use a modified version of SIFT which could do the task, but also

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be cost efficient. ORB is one such alteration of SIFT. ORB stands for Oriented FAST and Rotated BRIEF. As the name itself suggests, the ORB is a fusion of two very cost efficient algorithms namely FAST and BRIEF. FAST stands for Features from Accelerated Segment Test. It is a basic yet highly efficient algorithm. The model first selects a single pixel, stores its intensity and applies a proper threshold for further checking and then the model moves on to a circle of 16 pixels around the first pixel. Now among these 16 pixels, the pixel with highest contrast is selected as the key point of that region. This is highly efficient for key feature extraction but the drawback in only using FAST is that it cannot determine the orientation of key point it detected, and if the orientation is unknown, there will be a problem in identifying that key feature in different orientation as the model will treat it as a new key point altogether. To overcome this we use the BRIEF part. BRIEF stands for Binary Robust Independent Elementary Features. BRIEF determines the orientation of the key points and also provides a dimension descriptor for each individual key point. The orientation is determined based on the vector forming from the corner point to the centroid. This orientation is crucial for matching problems and hence also stored along with descriptor for further use (Karami, 2015).

The brute force matcher uses KNN machine learning algorithm for matching the images (Ben Amor, 2013)[11]. The brute force matcher is a very basic matching algorithm. It uses normalized Hamming distance for the determination of the nearest neighbor and based on the result of its calculation, it gives the output in sets or pairs of index of descriptors. For example, if A and B are two descriptors arrays, the brute force matcher will provide output as (i,j) where 'i' is an index of a descriptor point of A that matches with the descriptor point of B which has an index 'j'. Then one can discriminate among the matches, as per the accuracy based on whether the distances matched are efficient or not. These matches are generally displayed with the help of matching lines that help visualize the similarities of the 2 images (Karami, 2015). The results are shown in figure below.

Figure 3. SIFT and ORB Implementation respectively



The above algorithms evaluated the results successfully, but as the dataset is increased the accuracy of the algorithm failed, which is very poor as our need is to maximize the recognition with maximum dataset. Hence the authors shifted our attention to other traditional face recognition algorithms like Eigen face recognition, fisher face recognition and LBPH and also some high-end algorithm like one shot learning. One possible explanation for the failure of above implementation could be that the corners that were detected were not all necessarily contributing in establishing a unique identity for the face of the person. The corner detection and matching models were only extracting features based on contrasts of the intensity values of the pixels which should ideally be useful for object detection applications, but to establish an identity based on this would be difficult. For tackling such issues, over the past years many reforms are brought about in the field of machine learning, deep learning and artificial intelligence.

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One such approach would be using keras models for establishing the identity of a person. Despite being mostly similar to tradition corner detection techniques, few keras face recognition models are well trained in identifying human faces. These are solely developed with intention of recognizing human faces for various purposes. FaceNet is one such pre-trained model offered by the keras toolkit. The results of using this model are so prominent that the Siamese one shot learning approach recommends users to use the FaceNet for extracting the encodings from the image (Schroff et al., 2015).

Unlike ORB and SIFT, FaceNet provides the user with a dictionary of encodings that it extracts from the images. The FaceNet is designed to identify the key features of frontal face of a person just like Haar Cascade algorithm. It extracts these key features and then encodes the neighbor pixels of these key points to avoid information loss. Now with the use of a unique loss function knows as the triplet loss which uses two image encodings of same person and one image encoding of a different person and determines the unique features of that person.

Another viable approach would be using LBPH. The most essential task for face recognition is to identify the facial features of an individual face such as eyes, nose, etc. The Eigen face algorithm where the vectors also known as Eigen vectors are extracted from the matrix known as covariance which is basically in layman's term is a basic dataset of the all face image subtracted by mean of the complete dataset. The Eigen face method was used to get the recognition done but the error rate was very high. Another one of the most important and simple algorithm is Local Binary Patterns Histograms also known as LBPH which was developed in 1996. Local Binary Pattern (LBP) is a very affective texture operator which considers the neighborhood pixel as a binary number by labelling the pixels by thresholding them (Ojala, 1996). Both under Eigen face and LBPH the lighting condition is very important need to be equal as the dataset generated and the algorithm itself is very largely dependent on the features of the pixel taken under consideration. Accuracy of the system may hamper but system still detects the feature. Due to the behavior and its simplistic nature of the algorithm it is one of the most popular algorithm and all the modern face recognizing algorithm used in the mobile devices are the algorithm derived from the similar idea. In LBPH, an intermediately image is created that helps representing the original image in a more effective way.

This is achieved with the help of window sliding based on the 4 parameters which are Radius, Neighbor, grid X and Grid Y parameter which helps extracting the features of the pixels in binary form. The Figure 6 shows how a window of pixels is converted to a decimal value to represent the window. It's done in following steps:-(i) The input image is converted into grayscale and stored. Within this image, a part of the image is considered by 3x3 window.

Originally, a database of 40 unique face without mask images was taken for this implementation. The dataset comprised of photos of the friends and family of the authors, but in order to increase the variety the, standard dataset of PyImageSearch reader dataset by Prajna Bhandari is used. The dataset required for the scope of this project must contain images of people without face masks. The above mentioned standard dataset contains 686 without face mask images in total. Now along with 40 mask less images of the author's friends and family that becomes a total of 726. Now face is detected in each of these images using the Haar cascade face classifier and 30 instances of each face is stored in a folder which will be used for training and testing of the model as can be seen in figure 4. This gives us a total of 21780 images.

(ii)The window is then converted to a 3x3 matrix of intensity value of each pixel. (iii) The intensity of the center pixel is considered as threshold. That value has 8 neighborhoods. (iv)This neighbor values are converted to binary values. This is done by replacing any value greater than the threshold with 1 and any value less than threshold with 0 (Stekas & van den Heuvel, 2016). These binary values excluding

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the center pixel value, are then considered as a whole to get the central value of the matrix, Thus at last of the process (LBP), a new image is formed which represent the original image in a better way. These steps can be easily understood by having a look at their flow which is depicted in figure 5.

(v)The generated image is divided into multiple grids each grid consisting of a 3x3 window of pixels. Each of this window is encoded into a single center value, now each of these center values are used to form a histogram as shown in figure 6.

Figure 4. Dataset of images of registered people

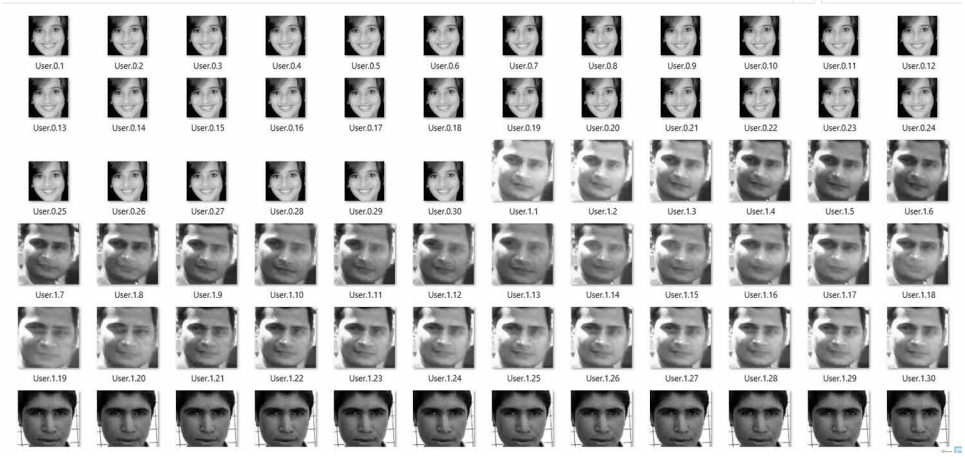


Figure 5. LBP Steps

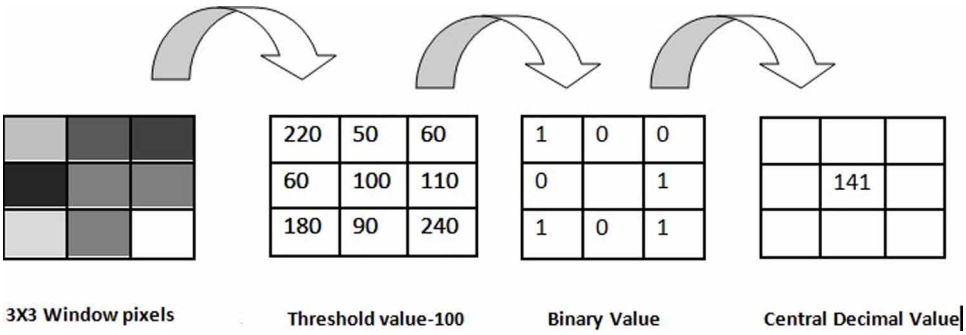
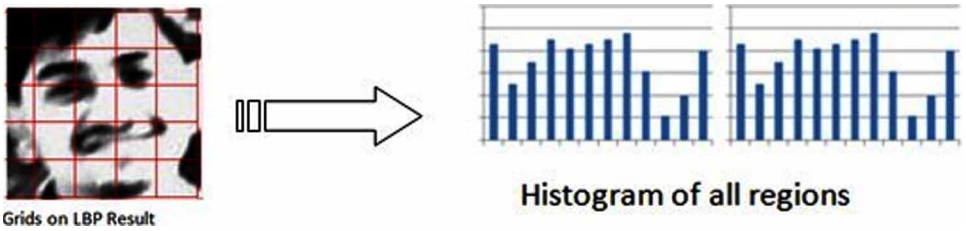


Figure 6. LBP combined with histograms



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(vi)The histograms are then extracted from that grid based image to represent the characteristics of the original image. (vii) Thus when our model is trained, histogram is created of all images in the dataset. (Ahmed et al., 2018) (viii) At this stage, the histogram of the test image which is plotted based on the center values encoded as mentioned above, is compared with the histograms of all the database images formed using the same technique. The comparison is done by simply finding the distances such as Euclidean distance, absolute value methods and other distance formulas. And based on these distances that are calculated, the match with the least distances is considered as the best match and the name of the person from the database is displayed (Zhao & Wei, 2017). (ix) Thus at the time of recognition when some features are hidden (as in our case) the histogram of the remaining features are compared, so there is no overhead on the system to feed the cropped image as the histogram take care of that part without laying much of the stress on the system (Naik & Guinde, 2020).

These are a few results of the face recognition model developed using LBPH. The result (figures 7 and 8) are a screenshot of live feed from webcam which is labeled after face being recognized. Also it can be seen in figure 8 that the model is capable of detecting and identifying multiple faces in same frame.

Figure 7. Results image 1

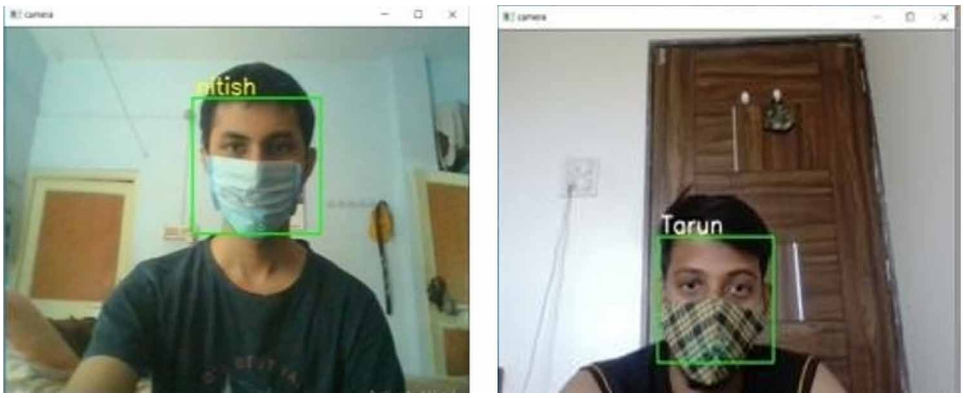


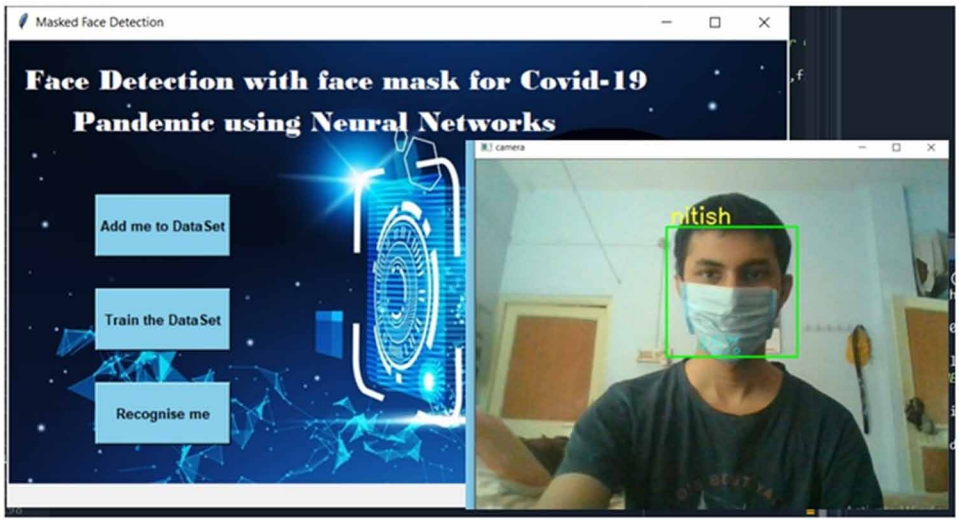
Figure 8. Results image 2



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The result of the proposed algorithm by LBPH was very affirmative and reliable. GUI making possible to generate, train and recognise the face at a same platform make it more user friendly and accessible. Multiple face detection and recognition is also possible at the same instant which can be very important in case of crowded place based application. The figure 9 shows the results that were achieved using the GUI. The physical devices or the normal face based detection where a person might have to remove the mask to expose the complete face might increase the chances of the spread of virus. In very critical application the proposed method can be integrated with some other algorithm and combined result may be considered to mitigate the error rate. The approach with modern algorithm can be revolutionary. Looking face with the perspective of the feature based on the facial orientation can make users to bend and develop the system as according to the will and need.

Figure 9. Final GUI implementation



V. COMPARRISION OF LBPH AND ORB

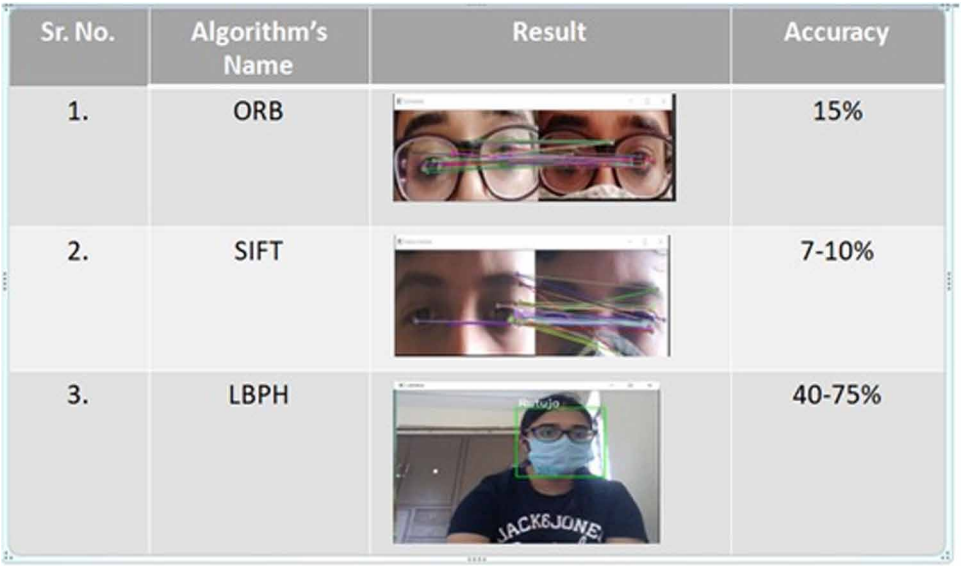
The result of both the algorithms used and implemented is shown above. Based on these results we were able to compare the models. The ORB implementation is faster, requires less computational memory and is really easy to implement. However, the number of features extracted from each image using this model is random because of how easily it is affected by the lighting conditions. This poses a serious problem as there is no consistency in the matching accuracy of this model. LBPH on the other hand, being more robust to lighting conditions' effects on the image, is highly consistent and has higher matching accuracy than that of the aforementioned.

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Table 1. Comparison of both models.

Features	ORB	LBPH
Database Size	50	1200
Features per image	20 - 50	85
Accuracy	9 – 15%	40 – 75%

Figure 10. Results of ORB, SIFT and LBPH



VI. CONCLUSION

The objective of the paper to be able to identify the masked face and to extract the features form the hidden face was achieved successfully. The mask was detected with the help of the neural network algorithm while the face recognition with a mask was performed using the LBPH algorithm. LBPH calculates the histogram for the all faces in the data set upon training and on recognising part the percentage of the feature or histogram matching with the person in front of the camera in real time is displayed along with the name of the person. The use of other possible algorithms was also explored and later it was concluded that the Linear Binary Pattern Histogram (LBPH) algorithm is best suited for this application due its efficiency and ease of operation. The accuracy of recognition was found to be around in the range of 40-75%, which is better than that of Oriented FAST and Rotated BRIEF (ORB) and Scale Invariant Feature Transform (SIFT) algorithms which can be clearly seen as an visualisation in figure 10. It was also observed that use of algorithm that highly focus on matching face features are difficult to deploy. It is observed that the use of the above implemented model is helpful to identifying people wearing masks in real time. This feature of the suggested model gives it edge over other traditional model and makes it more viable and preferable to be deployed in highly crowded areas for security surveillance. Therefore this implementation of masked face detection can be very helpful, especially during the current Covid

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times and can help the current system very efficiently. Also for other flus such as H1N1 virus which is also commonly known as Swine flu and other similar flus which spread through air and to avoid which a face mask is necessary.

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Chapter 13
Healthcare and Cyber Physical Systems

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ABSTRACT

In several facets of our daily lives, including how people access and receive healthcare services, the revolutionary trend of Industry 4.0 has been introduced. The fundamental innovative structures of smart healthcare galaxies are mounting in dimensions as well as density when we change in the direction of Healthcare Industry 4.0. Aimed at creation Healthcare Industry 4.0 significant enormous, composed information are accurately treated. As per requirements in place system offer helpful knowledge in addition recommendation. Nowadays we are going into the period of imaginative specialized arrangements. These arrangements assume a significant job in the development of the country like Cyber Physical System (CPS). Cyber Physical System is using in healthcare. Today's world-wide major issues of healthcare is coronavirus disease covid-19. This study emphases on the forthcoming growth commands beneath the Industries 4.0 and highpoint precise the growth strategy of healthcare. Moreover, the security and privacy of Cyber Physical System are discussed for secure CPS System.

INTRODUCTION

Industry 4.0 perceptions with know-hows employment as well as incorporation in healthcare is prospective benefit similar the further facility trades. At this time, Cyber Physical System is one of the emerging technologies. CPS is a prevailing aspirant for healthcare application which is used in hospital or in home for patient care. To provide fundamental roles of healthcare organizations, Healthcare incessantly enhanced by the universal penetration of industry 4.0 technologies. Smart digital settings are using in traditional hospital via organized sensor structures and data assortment and processing methods. Smart, low-power and wirelessly linked medicinal equipment provide the basis for Smart Healthcare. These

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devices incessantly monitor, process, record and guard the biometric information composed by detector, together with body position, weightiness as well as activities, sleep superiority, blood pressure, saturation of blood oxygen, body temperature, heart rhythm and pace, blood oxygen, levels (Zhang Y,Qiu M, & Tsai C. Hassan M.M.,Alamri A. 2017) of exhaustion, breathing speed, etc. . To offer an improved atmosphere toward individuals, this study emphasis on emerging several applications built on the CPS Healthcare. For treating patient, CPS healthcare are collectively involved life critical, context-aware, networked systems of medicinal devices. Today's world-wide major issues of healthcare is coronavirus disease covid-19. Considering such type of dieses Superior courtesies essential to be paid to stock and accomplish the massive capacity of information collected from thousands of people. As medicinal facts can deliver valuable intuition into treatments essential to except a patient's life expectancy. Through CPS healthcare, if all data voluntarily obtainable and available to approved medical persons all time from anywhere then it will be helpful to prepared vaccine and treat patient of dieses like COVID-19. The need to project multifaceted CPS healthcare system that are harmless and operative.

System is expected to face various challenges including high level of system software assurance, interoperability, context-aware decision support, autonomy, privacy and security and certification, such as the COVID-19 disease. It should be flexible and extensible to provide protection, safety and efficiency for all the processes designed for the broad usage of Cyber-Physical systems in medicinal organizations. The responsiveness capabilities, that is major factors for Cyber-Physical device delivery, make wireless sensor networks a significant part of Cyber Physical Systems. Cyber-Physical technologies are outstanding applicants aimed at in hospital and ambulatory healthcare due to the rapid growth of WSN, cloud computing and medical sensor systems. A rare development like the dispersed computation, cyberspace technology, scheme organization and hardware growth have created cloud computing maturity.

Through the integrated detector organizations and information assemblage, traditional hospitals are transformed into intelligent digital world of the next decade. From this viewpoint, Smart Healthcare is a dynamic ecology of intelligent environments e.g. clinic places, ambulances, chemist's etc. that supports a strong technology pile with control strategies as well as detectors, networks, fog services, in addition driving the medical devices of the Healthcare Industry 4.0 through creative business models and legislation. These devices incessantly monitor, process, record as well as defend the biometric information poised by detectors, with body posture, mass and actions, sleep superiority, blood pressure, saturation of blood oxygen, body temperature, heart beat and pace, blood oxygen, levels of exhaustion (Zhang Y, Qiu M, & Tsai C. Hassan M.M., Alamri A. 2017), breathing speed, etc.. This led to internal spaces and equipment of hospital like beds and wheelchairs being transformed by CPS. Hospital employees are given the ability to remotely receive, view biometric info on their machines and or mobile devices while doing their regular duties. In this way, physicians will take decisive decisions to save lives. Fusion data from many sources—is handled by a physician who uses his expertise to detect/prevent a potentially critical situation.

BACKGROUND

In this chapter. The authors discuss the medicinal equipment are currently available with what kind of technical support is needed. Novel observation frames embedded as well as mounted equipment are being developed and linked towards the Internet, most of which are IoT. Such gadgets will behave in the same way about this actual reality. Industry 4.0 is extensive in addition surrounding by its requests becoming

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important fragments of the diverse creation, engineering, and facility provision across diverse productions (Alloghani M., Al-Jumeily D., Hussain A., Aljaaf A. J., Mustafina J., & Petrov, 2018).

Improved tracking wireless sensor networks Increased diagnostics and patient care practices, Supporting personalised medicine prospects, Electronic health records, Mobile health apps. The study reinforced the greater influences of Industry 4.0 on the healthiness, education, and commercial sectors. Industry 4.0's business application has been studied extensively although the same technology application is obscure. In addition, the implementation of these structures lacks experience and manpower.

- A centralised data collection layer will be introduced to integrate community medicinal as well as individual healthiness resources.
- A cloud and data-driven (Zhang Y, Qiu M, & Tsai C. Hassan M.M., Alamri A., 2017) framework is created to store and analyse heterogeneous data from the multisource healthcare; and
- A cloud for medical application services is built that provides developers with a Unified API and a Unified User Interface.

Recognizing and instigating abilities can be inevitable, allowing wonderful collaborative circumstances between the actual and the recurring events. This prepared gadget energy will drive the versatility requirements of big data systems very far. This will increase a host of certified knowledge, fundamentally enhance applications and increase their awareness of what, logically, happens everywhere in this present reality. With a specific aim in mind, novel information processing and machine learning systems are essential from such enormous information spill. Cyber Physical System system's and platform emphasis toward CPS-based healthcare (Dey N, Ashour A. S. , Fuqian S, Fong S., Joao Manuel R. S. Tavares 2018) .

Sufficiently appropriate data collected from different sensors in heterogeneous CPS circumstances is the source of CPS intervention to abuse certain sensor/web phase assets and transmit the innumerable CPS conditions to complex business organizations. In the late written work, the overall approach was taken into account with assorted data streams beginning with devices or societal streams. For example, set-up focused coordinating stages for IoT (Zhang Y, Qiu M, & Tsai C. Hassan M.M., Alamri A. 2017), massive sensor data organisation based on cloud developments (Kashyap P. 2017), or managerial approaches have been tended towards managing gigantic, recognised cloud data (Dautov R, Distefano S, & Buyya R.2019). A key goal of Big Data in CPS is the separation from today's conditions of generous, fast and heterogeneous data sources. Machine learning can be distinguished data. The most widely apparent method to understand information through dada is machine learning. There are currently two important methods for the enormous data of the machine learning.

The novel visualizations with characteristics of the CPS-based on Healthcare System for secure system. (Yang G., Pang Z., Deen M.J., Dong M, Zhang Y. T, Lovell N.,& Rahmani A.M. 2019),.

The methods are from one perspective, for example the Hadoop and MapReduce represented, using distributed systems. The greatest typical programming plan is a framework of open source for machine learning in bunch environment. Several figures were ported onto a central hub to continue to run in parallel. Usage of Big data for Cyber Physical System must be vertically motivated towards cover a large number of data streams by correspondence. CPS must also concentrate the heterogeneous data properties, with a certain objective in order to foster the conglomeration and interaction of various sources of information. For example, in the case of anonymization, data respectability, and confidentiality, CPS needs to understand security and safety problems, as the big data distinction for CPS includes accurate fundamentals and entities, which thus have a special influence on our daily lives. By observing existing

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literature not pursuing Real-Time Big Data (Kashyap P. 2017) resolutions intended for CPS powered device structures is not met. Our job now is to look at all of our computation options for medical device manufacturing based on CPS. Real-time large-scale data theory method for the CPS Association of Medical Devices in theoretical terms seeing as in three stages, first is a CPS based device, the second is a control system (Rizwana P, Rajasekhara B M., Balamurugan B., & Suresh 2018) supported by the IoT and the third is a method for computing big data streams in real time (Dautov R, Distefano S, & Buyya R. 2019) producing a related intermediate layer context to proposals the communal facilities to the requirements inventers and enable the combination of diverse facilities to build applications beneath the Health care (Al-jaroodi J . Mohamed N., & Abukhousa E. 2020).Framework which permits humanoid performers to be semantically signified as well as recorded, composed through IoT objects (Şahinel D.,CemAkpolat O., CanGörü, FikretSivrikaya , & ·SahinAlbayrak, 2021).

CPS HEALTHCARE SECURITY & PRIVACY

In this context, safety is a key related as infected person information legally and ethically confidential. Therefore, careful attention must be paid to ensure data protection during the design of CPS architecture for healthcare applications. CPS safety especially challenging in the occurrence of physical communication, control System, and accessibility (Wankhade M, & Kottur S.,2020 b).

Health Guard regards malicious device behaviours, which may lead to an unusual functionality of Health care System (i.e., an unauthorised user who changes the device states). The potential attack scenarios for our work are described in. It considers the disruptions and disclosure resources of the attackers' device model. Disruptive means allow an assailant to influence system activity and accessibility while discovery of resources allow the intruder, while breaching data confidentiality, to receive delicate information about the system. Comparative study of different framework to have the best performance of the Cyber Physical System and diverse safety constraints are estimated based on the model (Wankhade M, & Kottur S.,2020 a). Awareness of the system model also gives an abuser near information on the system to attack more complexly. The authors have chosen three categories of assaults covering all three assaults features.

Threats model consists of manipulated medical devices, Denial of Service attack and injection of incorrect information. When an assailant knows about a preceding scheme, false data injection can be attacked by his disclosure tools. DoS attack disturbs the resource, while a manipulated computer attack may trigger both disruption and disclosure. In the following the authors categorize the threats:

I. In the environment, a malicious attacker may be found, and fake information inject to conduct malevolent actions in the direction of alter a patient's physical condition. This threat is a false injection of data in a medicinal instrument.
II. Any medical system may have a malicious software installed so that the device will not go to sleep approach which is a manipulated computer assault.
III. An intruder can be present in the area physically to disturb any medical device to temporarily make it inaccessible. Such risk is a Denial-of-Service attack.

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CPS Healthcare Privacy.

The healthcare professionals are bound by the confidentiality of patient doctors and the protection of patient information. In health care there are continually growing numbers of sensors, facilities, and personally identifiable patient data. All these measures are a burden because the design of the device cannot act in future unidentified circumstances. Ensuring data protection from application and data level is an important problem.

In medical applications, multiple users and clinicians are involved; interaction between them must therefore be ensured. Whereas authentication protocols protect cloud servers, user-level encryption of data offers greater security. Unauthorized data access and data corruption can be detected using mechanisms. The observation canters are believed to be a central command specialist which cannot be manipulated by an opponent.

HEALTHCARE APPLICATION OF CYBER-PHYSICAL SYSTEMS

Cyber Physical Systems are used in a wide range of areas: traffic, safety, automobile, manufacturing and development controls, energy efficiencies, environmental monitoring and administration, engineering apparatus for robots and biological systems, etc. (Sultanovs E, Skorobogatjko A.,& Romanovs A. 2016). Comparing use in these areas with use in medicine the most precise, concise and enormously nominal likelihood of error must occur for Cyber-Physical systems in medicine. Systems designed to benefit people cannot damage their fitness. CPS healthcare should also be reliable, secure, and effective for people.

Diverse applications such as hospital, supported living, as well as ageing attention are offer by CPS in health care. Subject to specific applications, system complication and essentials in construction need special design. For functioning decision making in CPS, smart devices in healthcare surroundings can provision the data procurement. Data acquisition is intended for combining the energetic participation of operators. CPS in healthcare provides a general description of the synchronisation of self-directed and adaptive plans and innovative concepts for the management and active physical systems of medicines, contractually implanted intelligent techniques, new design approaches, body area networks and programmable assets.

Supported and Precise are two categories of application in CPS healthcare. In Supported application, deprived of limiting individuality in an individual's regular existing supported application embraces the health monitoring. In the direction of medical assistance to specific patients is probable through obtaining physical information by biosensors in actual stretch. It is probable towards provision in addition attention growing numeral of ageing individuals in cooperation in ageing existing and specific families through the discrete medical necessities considered into account. In-house protection and autonomy can be attractive for computing technologies.

In precise application, its environment involves of hospital in addition rigorous attention wherever the medical provision is willingly accessible. Data from numerous causes is mutual to direct intercessions. Developing skills goal disenabling isolated attention of patients will offer attention consultants through data in what way actions of regular active move fitness attention also permit consultants to variety additional knowledgeable conclusions around intrusions. These two types of healthcare would convert into Cyber Physical System with numerous advantages and challenges.

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ARCHITECTURE

Cloud, Big Data, and machine learning are (Kashyap P., 2017) critical strategies in the healthcare sector and are also progressively becoming the innovation trend in healthcare. Today, medicine relies far more on the processing and review of precise data as medical information is increasing explosively. Thus, published, and shared medical information through the cloud is common in practice. Usually, patients know better than a physician. As such, the cloud will enrich and distribute the information and knowledge base. Affected role can likewise engage vigorously in large-scale medicinal operations supported by big data. Two aspects of Cloud Computing are interesting towards the end users; first, handlers can access private information and applications by any computer associated to the Cyberspace, and, second, software applications are not essential to be installed in the operator's computer and they are available on the cloud (Haque S. A., Aziz S.M.,& Rahman M,2014).

The medical right is restored to patients by way of cloud computing, smart phones, wireless sensors, as well as the job of a doctor is to provide patients with supporting decisions. Big data in addition Cloud revolutions may consume a major effect on the health sector, that is even transformed into a new dynamic situation (Zhang Y, Qiu M, & Tsai C. Hassan M.M., Alamri A. 2017). Figure 1, shows the extended health care system that is more appropriate.

Architecture essential to be established to offer Cyber Physical System for healthcare request as per user data obligation, system incorporation and request province in CPS healthcare. Structure, data prerequisite and configuration are the three elements of CPS architecture for healthcare. Structure of CPS healthcare designed are server or cloud based. Small structure is appropriate for server based with individual care necessitate. The cloud-based structure intended for scalability, cost efficiency, and availability. The Big data placed calculation services, the actual big data calculation aimed at CPS related medicinal appliance connotation (Rizwana P, Rajasekhara B M., Balamurugan B., & Suresh 2018). Data prerequisites for health care include various types of data for managing CPS architecture, such as input data, historical information, and output data. The data size of the biosensor form can be different for healthcare. Simple data such as temperature can be available, although large image data such as MRIs(Magnetic Resonance Imaging) also need to be addressed. Light and heavy data types can also be classified as the data requirement. The requests essential to be collected either dynamically or as per system formation or handler's prerequisite. System Architecture will be able to identify rendering system configuration on request. The proposed smart checklist will help and direct the individuals associated with work. The scheme is similarly strengthened with communication with the plans and programme requests.

DEVELOPMENT PROCESS

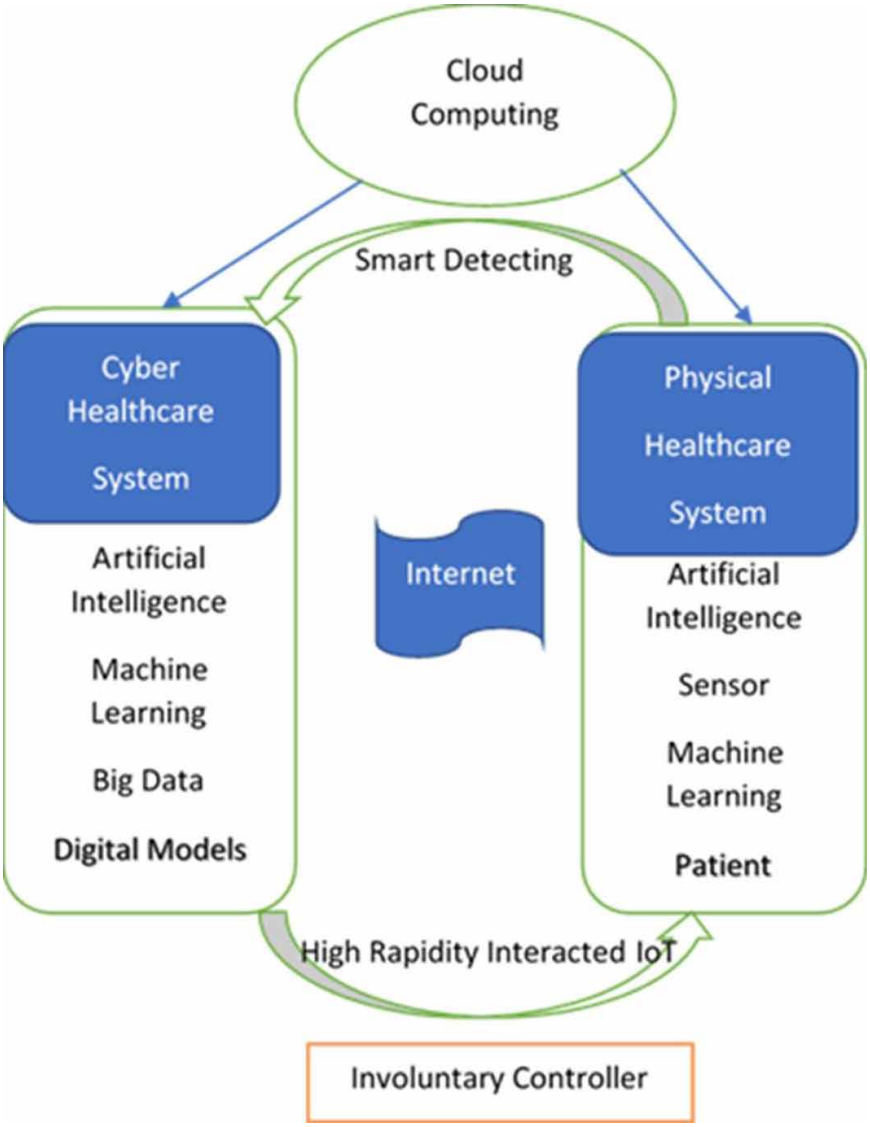
The Cyber-Physical system of this type of process can't be understood starved of the contribution of a unlike area experts, that can regulate organization abilities to the essential equal for the arena of usage. Development process of Cyber-Physical system required Information of computers, software system, and corporal procedures. Cyber-Physical System used in the health care requirement provision extensive variety of info conversation values that is utilised via the maximum of present in addition pathologically beneficial strategies that accepts as well as procedures patient's healthiness state info. To accumulation info of patient's fitness state pointers, arrangement necessity differentiates info foundation, and origin faith level that can be assessed by specialists, that would permit organization to quantity information

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consistency and brand choice approximately an info additional procedure. Standards for medical equipment have been established to improve efficiency, numerous services, and interoperability of equipment. It should be stressed that only accredited Cyber Physical devices should be in use in healthcare facilities. Modelling, design, and analysis are the three process which include in CPS design. Each CPS model is intended to report a precise problematic or comprehensive a mission.

The prescribed definition diminishes the numeral of incidents occurring, but modeling is an example. The degree to which the device has fulfilled the criteria may be calculated during the review phase. In compliance with previous and current conditions, CPS shall be commissioned or modified.

Figure 1. Illustration of Cyber Physical System in healthcare



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The Cyber Physical System utilized in the healthcare sector requirement accept the broad assortment of data sharing requirements which are used to obtain information about patients' health status from most current and medically useful devices. The system must differentiate between the source of information and the source of trust level that experts may assess, to measure the reliability of the data, and to decide on future use of information, in order to store patient health information in a patient status indicator. The design of the Cyber-Physical framework should be focused on common behavioural system demonstrating with software, hardware, web and physical procedures. A Cyber Physical System is a reiterative aspect development consisting of three stages: Demonstrating, Design and Testing (Sultanovs E, Skorobogatjko A.,& Romanovs A. 2016). The real-world research should be done first, as well as physical processes, which communicate with Cyber-Physical system, to create systems that can perform in the real world. The expandable as well as difficulty of CPS complex the tasks of traditional systems to encounter a enormous request for quick growth of flexible and reliable networks (Unal E.,Sen-Baidya S.,& Hewett R.,2018). The next step is the creation of an abstraction of the processes in the physical world. A model strategy permits nearly basic difficulties like safety, determinism, and time to be resolved in the Cyber-Physical design of the system. In a phase of application, new preferences, needs and expectation can emerge for a Cyber-Physical device. All medical devices are covered by a number of legislation and guidelines that express the device is protected for the end user (Sultanovs E, Skorobogatjko A.,& Romanovs A. 2016). Cyber-Physical device sensors produce confidential information which can only be securely secured as well as distribute.

The knowledge of CPS production processes involving devices, applications, networks, and physical processes that is incorporated into the system. Cyber-Physical framework covers necessities administration, plan administration, examination, and protection strategy, with all implanted system inventiveness processes. Real-time operating systems are controlled to operate embedded systems. Technically sophisticated low-level design is needed for the creation of CPS, that communicate thoroughly by corporal procedures. CPS designers are required to deal with disruption regulators, storage construction, process development, programming of assembler levels, network interface design and driver installation. However, the functionality and definition of behaviour of the device is better to focus. There are currently no guidelines and legislation specifically related to Cyber-Physical healthcare systems. However, guidelines, legislation and clinical standards on medical equipment are worth knowing. In some nations, legislation for medical devices are similar, but not the same.

METHODOLOGY AND EXPERIMENTAL DESIGN

General Structure of The Proposed System

CPS Healthcare System denotes to a medicinal instruments or collection of medicinal instruments associated through a variety of physical sensors to gather information from the affected person's body as well as backgrounds and make self-reliant conclusions to deliver better therapy. The insertion of info and allotment among patients and providers of health services using wireless and wireless technology improves access to health care, improves care quality and enhances overall health care performance. As previously discussed, the intelligent healthcare system can be a singly or numerous intelligent medicinal instruments such as wireless strategies, implantable equipment, wearables, etc.

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CPS healthcare also considers various non-medical criteria in addition to these devices to correctly diagnose a case (disease, body condition, etc.). In this case, the machines capture various critical symbols of the patient, to understand the patient's overall health. These vital signs and their nominal values are interpreted as analogue signals in which vital signs are collected, tested and digitised for transmission into the processing unit as network packets. In accordance with the vital signs transmitted by CPS healthcare, the processing unit monitors patients' general state, reports the doctor in case of an emergency. In some cases, autonomous decisions are often taken such as proposing the new medicine, changing the dosage, etc. For instance, the oxygen level monitors the patient's neural activity and the cardiac condition. When a patient's body behaviour or condition changes, Electroencephalograms (EEG) and electrocardiograms (ECG) indication outlines are changed. A medical specialized may observe and interpret this as a cardiovascular issue by observing the Electroencephalograms and electrocardiograms indication change. CPS health care can also be designed to identify various pre-defined conditions and provide the patient with autonomous treatment.

Unified Function of The Body

The activity of various body part in the humanoid system are interrelated, which influences the overall state of the human body, if any organ acting abnormally. For example, if the cardiac rates unexpectedly increase in the body, they can cause heart palpitations, shortness of breath, etc. Since CPS Healthcare can simultaneously monitor various body functions, this relation can be identified and used to determine the source of the issue. This body interconnectedness as a feature of CPS health care to detect abnormal behaviours. When we discover, for example that a patient has decreased oxygen level, breathing increases and certain waves of the brain change in patterns, etc. Headache, restlessness, dizziness, quick breathing, pain in the thorn, nausea, euphoria, rapid heartbeat are recognisable causes.

This scenario shows the decline in the oxygen level of a patient by the observation of the critical signs gathered from the electroencephalogram, oxygen observation, pulse oximeter and blood pressure, glucose observation, sleep surveying devices.

Study of Anomalous Behaviour

A model that describes all normal behaviour of the system to distinguish abnormal behaviours is called an anomalous behaviour analysis. The ability to identify unknown attacks makes it ideal for an intelligent healthcare safety system. The main challenge, however, in the implementation of such a method of analysis in CPS healthcare is to define the basic reality of usual behaviour through a small wrong positive rate. The authors suggest that an anomaly in devices based on patient health conditions and behaviours should be analysed to address this issue. For example, a person who works in a gym is increasing the heart rate, decreasing the amount of oxygen, increasing the respiration and changing patterns of certain brain waves. A safety mechanism should recognise continuing action in the humanoid body and assess whether the action was good or malevolent founded on vigorous symbols obtained from the linked intelligent healthiness equipment's in order to detect abnormal behaviour in a CPS healthcare system. In understanding benign behaviours and identifying disease conditions in a CPS healthcare, the authors recognise various everyday handler actions and the vigorous symbols of the human organs for sicknesses. An alert abruptly occurs in a blood pressure control device when a person is taking high-cholesterol food who don't have high blood pressure because they exceed the minimal threshold of systolic 120. In

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this chapter observation of consumer behaviour and usage trends for the basis of the health guard takes into account the normal and disease-impaired interface scenario.

Problem Scope

The authors adopt an affected person who permit entry to a clinic consuming chest aching aimed at a couple of days to grasp the problem scope of our work. To track emergencies, many smart medical devices are installed with CPS Healthcare that observes various vital patient signs. For instance, an ECG, pulse oximeter and EEG heart monitoring unit are put on patient to display blood level of oxygen and brain nervous system movement correspondingly. Furthermore, the authors presume that the equipment performs perfectly and that the machine instals no affected device. Finally, the device is designed to notify the doctor and to advance the medication if a unexpected alteration in the patient's heart occurs. The ECG began to inform the physician of the sudden fall in cardiac rates at some stage. Though, the vigorous symbols of electroencephalogram as well as pulse oximeter are regular, and not any changes in heart rate are observed by the patient.

As a novel safety mechanism, this chapter is presenting Health Guard that can evaluate CPS Healthcare's overall status and decide if a malicious incident took place on the system through Health guard is used.

Module for Information Collection

The Information Collection module gathers information from various CPS Healthcare medicinal equipment's. There can be several devices in a CPS healthcare system, which can be linked to a network and operate collectively. The data collector module from these devices collects and stores the essential signs and condition of the patients in a database. The collection of features extracted from the device transmitted to the sampling and data merging pre-processing module.

1. Collection of Data

The data collection in the CPS Healthcare refers to various data collected in parallel in the artificial intelligence algorithms from a number of sources. The following sources may be:

a. Patient

The patient's information comprises various physical signs such as posture, electrocardiogram, skin temperature, Electromyography, blood glucose or breathing rate, pulse oximeter depending on the application of the health monitor. For instance, the data on electrocardiogram, gait, and respiratory rates will benefit shaking, stiffness, and difficulty with walking, balance, and coordination disease patients from gait monitoring system, but not so much from electrocardiogram (Shishvan O.R., Zois D.S.,& Soyata T. 2018) when monitoring cardiovascular conditions. In practise, skin-worn sensors available for the commercial use have the capacity to measure a range of physiologic signs, and are constantly being built with advanced bio-sensing capabilities.

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b. Exterior Information

Additional data, including ecological data, can be utilised in Contextual applications in adding to information obtained from the affected person's body. This supporting data contains details on the patient's condition as the data is collected. For examples, include the use of physical devices which accumulate various parameters such as acceleration data, audio data (Shishvan O.R., Zois D.S., & Soyata T. 2018), wireless link and times of the day to track patients who are experiencing a certain amount of mental and physical impairment. This application will locate the patient, determine whether the affected person is unattended and their current physical activity (Shishvan O.R., Zois D.S.,& Soyata T. 2018) by means of these parameters .

c. Historical Data

The provision of data for machine learning algorithms can be invaluable in a series of longstanding affected person healthiness histories, held either inside the clinic housing the initial patient surgeon or another sickbay. An example of an individual healthiness record containing the medication the affected person takes, the past of indications related to different medicinal problems, a list of physician notes as well as laboratory test results can be found in a sample medicine record.

DATA PROCESSING ALGORITHM

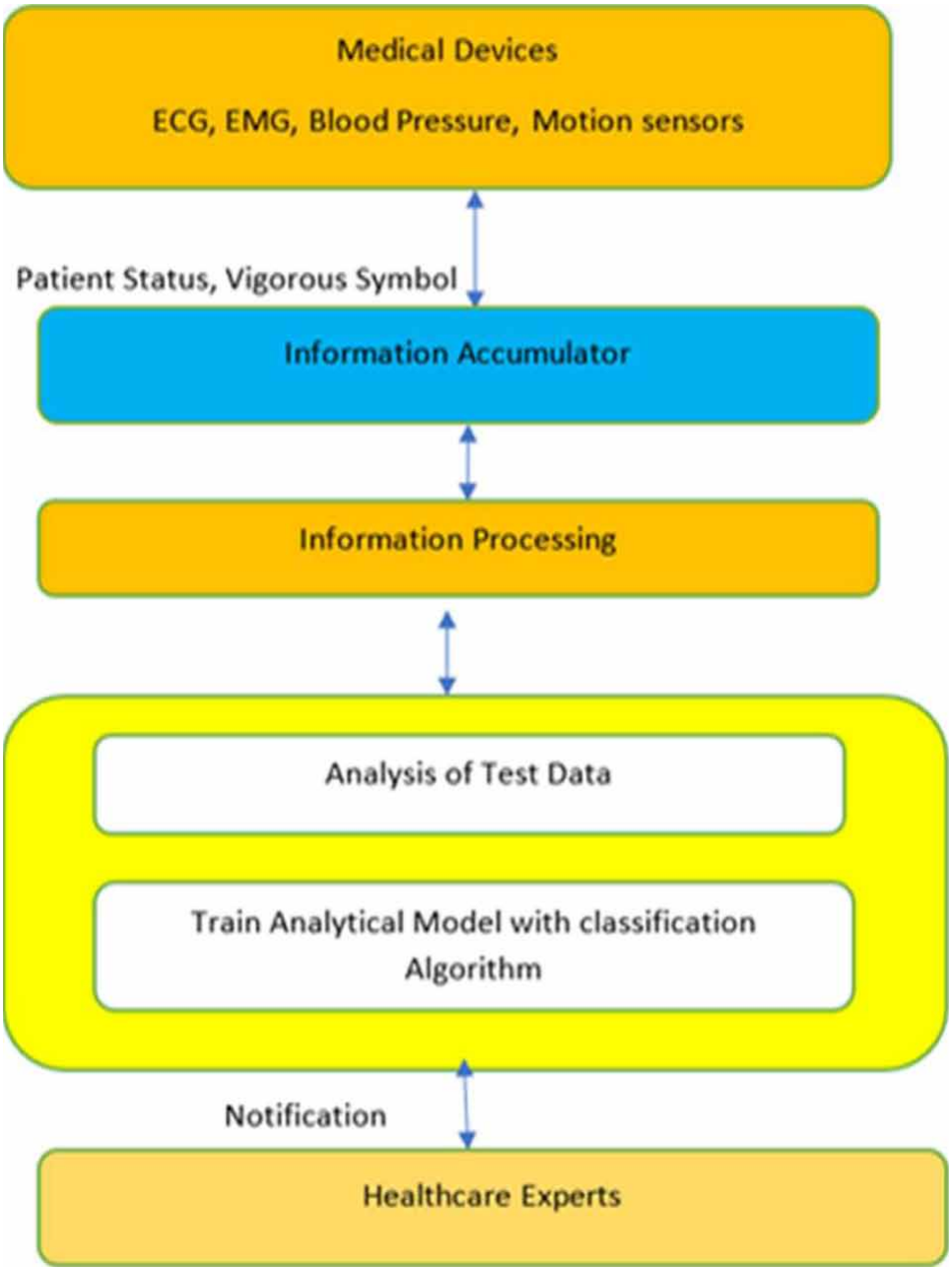
In general, the analysis of large and complex data sets involves considerable memory and computing resources. At the same time, repetitive and non-discriminatory use of a large number of variables has a negative effect on the classification of algorithms by overcoming problems that lead to weak generalization. Prior to transmission of the acquired patient data into the cloud, a nearby computer-specific system performs extraction and feature aggregation steps in the handheld cloud computing. Figure 2 shows Process of proposed data processing algorithm for Cyber Physical System healthcare system.

Statistics flow comes continuously and processed in actual time. when facts are gathered from every acceleration sensor, it's first of all filtered via the utilization of an IIR (Infinite Impulse Response) bandpass filter through a reduce-off occurrence in order that it'll postpone somewhat reference line offsets and high frequency noises. Value range recognition algorithm is calculation effectual to eliminate any artifact records whose values are out of scope about a representative operational data.

A machine learning knowledge of classifier is applied for evaluating the likelihood of ECG Measurements Values of every era Key capabilities are take out from era and are attended as enter trail to the classifier. The system gaining knowledge of module are often skilled through skilled patterns, accordingly can mainly raise device overall presentation via precisely deciding Classification algorithms which don't need heavyweight control. on this context, Cyber Physical System device model lies in its additive knowledge capacity, in order that it is feasible to hold out non-stop integration of recent incoming instruction styles without disastrous overlooking of what it's educated beforehand. clinical records are notably tough to accumulate as related to statistics from different disciplines, along the assist of additive education, as soon as novel working out styles are accessible, additive mastering permits the classifier to review novel statistics from statistics on any occasion deprived of re-education the entire classical from the start.

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Figure 2. Process of proposed data processing algorithm for Cyber Physical System healthcare system



MEDICAL DATABASE

This everlasting record includes information on the inaccessible controlled patient, and altogether medicinal information of additional affected person that the same health care organisation is looking after. The possibility of machine intelligence algorithms performs better with a data base that contains a huge number of affected persons with alike healthiness problems.

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EXPERIMENT AND RESULTS

Inside test, the classifier-learning system was primary skilled through beforehand labelled education patterns. The device then operated on novel records that were no longer part of the education statistics set. This novel sign changed into noted deriving out of a

patient with the aid of using the healthcare Cyber Physical device sensor on recording mode. E-Health Sensor Shield device shown in figure 3 and Electrocardiogram with wireless communication device shown in figure 4 are used to collect patient data into a Healthcare Cyber Physical System. The investigational outcome about planned system on this offline fact is shown in figure 5, figure 6, and figure 7. Figure 5 shows Electrocardiogram measurement value – RR interval observation. Figure 6 shows Electrocardiogram measurement value – heart rate observation. Figure 7 shows Electrocardiogram Measurement Value – QRS Duration Observation.

It is far found that the gadget has as it should be diagnosed ECG Measurements values movements placed with reference to RR intervals (in seconds), Heart Rate (Beats per minutes) and QRS (in seconds). It helps to monitor the patient status and take correct action by care taker and healthcare professional.

Figure 3. e-Health Sensor Shield

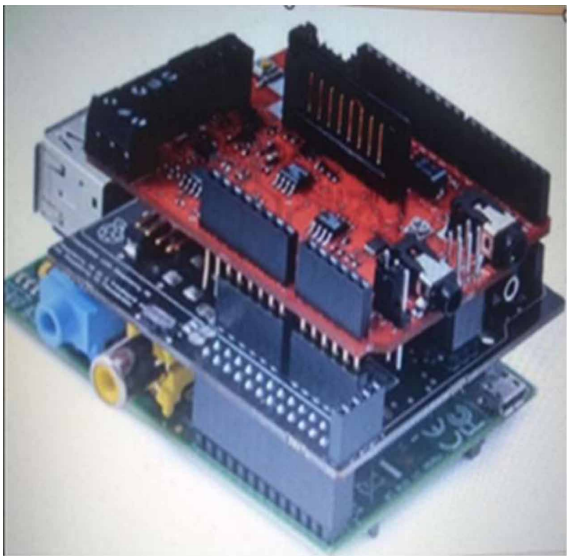
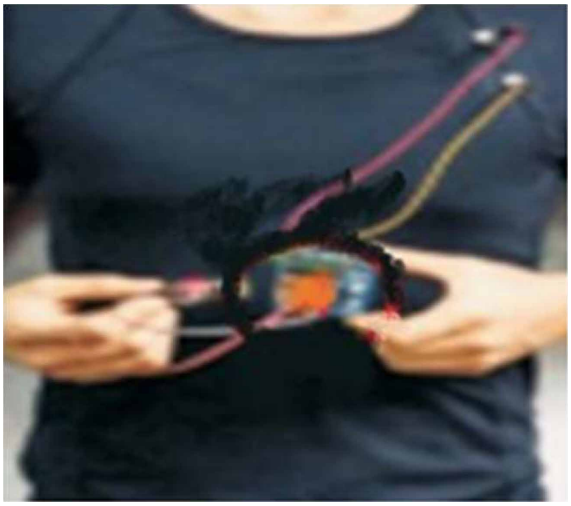


Figure 4. Electrocardiogram with wireless communication



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Figure 5. Electrocardiogram measurement value – RR interval observation

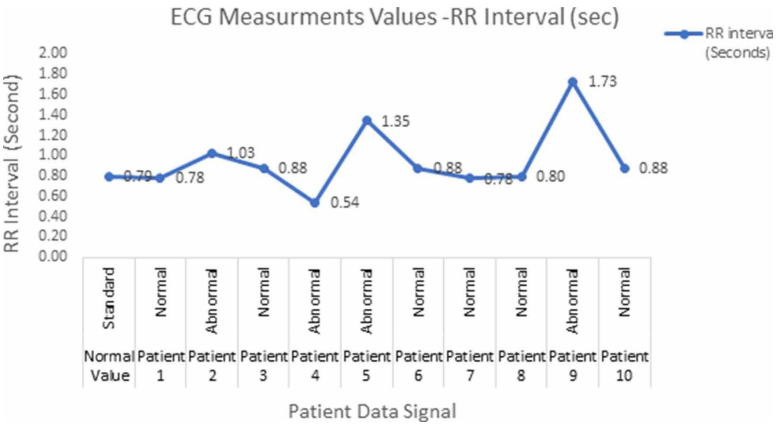


Figure 6. Electrocardiogram measurement value – heart rate observation

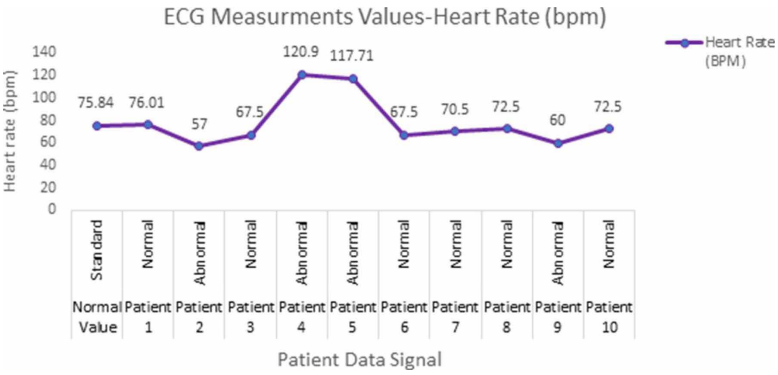
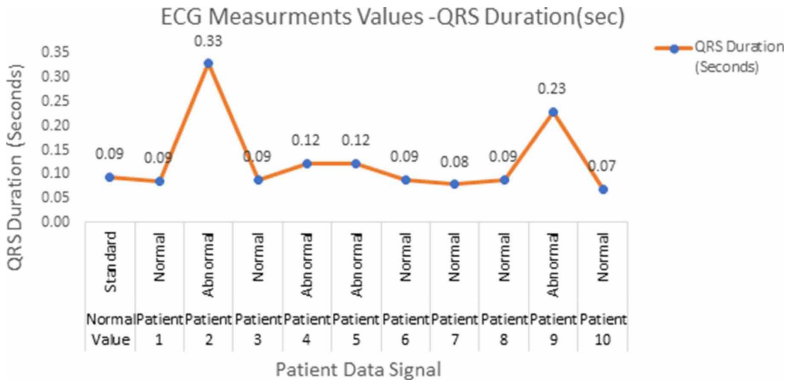


Figure 7. Electrocardiogram Measurement Value – QRS Duration Observation



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FUTURE RESEARCH DIRECTIONS

In this chapter, security and privacy problems are recognized by way of the slightest discovered in Cyber Physical System intended for healthcare system. security and privacy have become more critical as well as significant for both CPS inventers and handlers. But there are numerous divergences between the demands of CPS and the existing approaches to security and privacy risk assessment. Therefore, in the area of CPS, required additional consideration to the combined risk assessment methods with respect to the context of safety and security in the future.

CONCLUSION

Intelligent healthcare systems provide improved diagnosis tools and treatment to patients but as mentioned in this paper, pose security issues as well. Healthcare will now reach Machine Learning, Cloud Computing, and Big Data technology. More specifically, the study of Cyber Physical System, IoT, cloud computing, ML and big data technology could be used as a lifestyle guide, as a method to help decision capability in addition origin of creativity for the changing environment of health care. This paper develops and manages the individual health effects of a model framework for personal healthcare delivery. This work is focused on the Healthcare and Cyber Physical System. The authors will concentrate on designing various health-CPS-based applications in future to provide humans with a great environment.

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Chapter 14
Impact of Human Mobility Trends on the Outbreak of COVID-19 Across Different States of India

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ABSTRACT

The explosion of coronavirus has posed challenges to public health infrastructure in India. This pandemic can be contained with social distancing and isolation. The analysis of human mobility trends plays a decisive role in the spread of the pandemic. These movement patterns are extracted from Google COVID-19 Community Mobile Reports. These reports help to analyze the human mobility trends to various frequently visited places across different states of India. This work focuses on analyzing mobility trends in India and their effect on the spread of pandemic in terms of number of active cases and death rate. The mobility patterns, number of tests conducted, population density across different states in India are explored to understand their effect on the severity of epidemic. These features are correlated using statistical methods. This study lays the foundation in building a framework to contain the contributors for the spread of pandemics and provide insights to the regulatory bodies to strategize enforcing or revoking lockdown restrictions across regions in the country.

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1. INTRODUCTION

The outbreak of pandemic COVID-19 has affected human life drastically. Social distancing and isolation were chosen as the effective strategies to control the spread of this disease across the globe. Human mobility is restricted across the globe because it can easily affect the spread of transferable disease and create threats to global health. Due to the threat of pandemic, many countries across the globe enforced the constraints on human mobility as this trend also results in social distancing to control the spread of the disease.

During the early phase of Covid-19, the number of active cases showed an increase day by day across many states in India. Indian Government thereby announced country wide lockdown in the month of March 2020 and adopted different policies for enforcing the restrictions of travel among the cities to stop the spread of the virus. Although the central regulatory imposed country-wide restrictions, the state authorities executed with different autonomy. Also, every state had diverse health infrastructure facilities, population density and socio-economic conditions of transferable disease.

Human mobility trends are indicators of social distancing and human movement. Mobility trends are generally analyzed as human movements to various places such as parks, stations, grocery shops, workplaces, recreational centers and residences. These, mobility trends are necessary to be monitored and analyzed to observe the compliance of lockdown policies and their impact on the spread of disease.

The challenge here is to empirically measure the human mobility and its study its effect on the spread of pandemic in different parts of the country. It also helps to get the insights of geospatial patterns on the spread of transferable disease. The population density also poses a challenge in controlling the disease as clustering of infected patients in a smaller terrain leads to more accelerated and uncontrolled spread. In fact, researchers pose that densely populated countries like India are more vulnerable to transferrable diseases inspite of restricted mobility trends. The severity of the disease is measured in terms of active cases at a given time and death rate. Death rate is defined as ratio of number of death incidences to the number of active cases at that point of time. The number of diagnostic tests conducted for the detection of disease also play a significant role in unveiling the number of cases. Population density is defined as number of individuals per unit area.

Our work studies the effect of human mobility trends on the number of incident cases and death rate with statistical evidence. The authors also present critique of how population density and number of tests conducted affect the spread of the disease. Although there is presence of research works in the area of mobility trends and its effect on containment of COVID-19, there is absence of such a study in Indian context. Also India presents diversities with respect to health infrastructure, political autonomy, population density and socio-economic conditions across different states in India which have resulted in different levels of spread of disease. Hence a work which analyses all the contributors to spread of Covid-19 together is a need for gaining a wholistic view.

The presented work contributes with:

1. Analysis of trends of the population in the states are studied for Grocery, pharma, residence, workplace and Transit mobility
2. Study of number of active cases of COVID-19 and death rate in the state are analysed as the causal effect of the mobility trends in that area.
3. A rationale on the compliance of the lockdown with restricted mobility across different states, is observed

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4. Building a statistical model that analyses causality between the significant mobility trends and the incidences of the cases with death rate in a particular state, is built.
5. Analysis of number of incidences of COVID-19 in a state with the number of tests as some of the states proclaimed to have discovered more cases with a greater number of tests.
6. Observing the impact of population density of a state on the number of active cases in the area.

2. RELATED WORK

The work (Charoenwong et al., 2020) shows the relevance of social connections towards the spread of coronavirus Social connectivity with the countries with highest outbreak of the disease indicates the probable spread of the disease. This is probable with the mobility trends amongst the people who are socially connected to each other. The social connections were captured with the anonymized Facebook data and mobility trends were captured with the mobile phone data. The mobility patterns captured by the socially connected group was called Safe Graph.In the work (Goel & Sharma, 2020), authors have proposed a mathematical model for the study of an epidemic turned pandemic with two important factors and that is the population density of a region under study and the connectivity of that region with the other parts of the globe.

This work (Dahlberg et al., 2020) also uses mobile phone data to trace the mobility of users of Swedish mobile phone network after imposition of less restrictive measures taken by the Government. The mobility trends were measured and used to find the reactions of the people with the percentage rise or fall in the household residence, workplace inhabitants and movements within a kilometre or so.In this work (Lee et al., 2020), daily movements of people in the US are captured from the mobile data and analysed to conform the trends with the regulations of the government orders. The work aims to present a tangible proof to the authorities and awareness to the people about the compliance to social distancing. Authors have presented the analysis for people staying at home as well as for the income group population.

Authors in (Fang et al., 2020) have presented a model to establish the causal effect of strict imposition and execution of the mobility restrictions in the birthplace city of COVID-19 Wuhan. The paper presents an evidence-based analysis that the strict compliance of the lockdown has been helpful in controlling the spread of the epidemic to the outside of the city and district. The migration data is based on the real time location for every phone. Movement between cities is majorly captured for establishing the facts. In this work (Chang et al., 2020), the intracity and intercity transits and their impacts on the spread of COVID-19 is done for the city of Taiwan. The paper discusses interesting facts of how intracity transits in Taiwan from a thickly populated and affected region have become more important in spread of disease. The work uses Facebook's aggregated and anonymized movement and colocation data to find the cities of higher risk and predicts a better plan for opening travels after the lockdown.

This work (Wang, 2020), presents the analysis of human mobility patterns specially residence mobility trends with stay at home regulation. The mobility patterns are extracted from COVID-19 community reports. The effectiveness of residence mobility in containing the spread of the virus is captured and the statistics is compared with the neighbouring states who have not implemented stay at home orders. The stay at home has been studied for its efficiency and causal relationship with the spread of COVID-19 virus. This work (Oliver et al., 2020) presents how the use of mobile data helps the US government and measures or actions to be taken to control the spread of the pandemic COVID-19. The authors present how mobile phone data can give valuable insights during the pandemic phases.

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In the initiation phase, the infected cases are detected. The mobility of infected individual, location, their social network is captured. In the acceleration phase, when the transmission outreaches to a certain level, the focus is on how to control the spread by enforcing the mobility restrictions. The mobile phone data is used to validate the effectiveness of policies. In the declaration phase, restrictions on mobility will be lifted and different measures to be taken to balance the spread of pandemic and also from the perspective of the economy.

In this work (Bergman & Fishman, 2020) the mobility trends from Google community report, Apple is captured, and the analysis of mobility patterns and its effect on COVID-19 cases is performed for all states in the United States. They employ a model for estimating daily transmission rate for different countries.

Authors (Lasry et al., 2020) in this work presented the analysis which suggests the enforced policies for increasing the social distancing is an important instrument which results in affecting the spread of pandemic. The data is captured with the help Safe Graph. In this work (Yilmazkuday, 2020) authors have presented the analysis of the mobility trend and its effect on COVID-19 deaths and pandemic spread. In the work (Rocklöv & Sjödin, 2020), authors analyse the impact of population density on the spread of pandemics in economically underdeveloped countries. Additionally, the work (McKibbin & Fernando, 2020) empirically prove that the population density catalyses the contact rate and thus leads to spread of the disease in thickly populated area.

Our study also aims to study the efficacy of the lockdown declared in all the states of India, their compliance and their causal effects on the incidences of the active cases of COVID-19 post lockdown 1 till the less restrictive phase of Lockdown 3. The time spans over a period of March, April and early May 2020 and other mobility trends of the people in different states of the country in this period are observed.

Very few literatures have analysed the mobility trends captured from Google mobility report for the study of spread of this disease. The study includes mobility, trends for grocery and pharmacy, workplace, transit and residence mobility in the majorly affected states of India. The authors have analysed the correlation between the grocery pharmacy mobility trend, transit mobility trend with the transmission of COVID-19 cases. Additionally, the work also analyses the clustered effect of the spread of the epidemic in thickly populated states of India.

3. METHODOLOGY OF THE STUDY

The presented work presents a statistical inferential modeling for finding significant contributors and data visualization for impact analysis. In this paper, the methodology is described with 3 artifacts.

I. Datasets II. Statistical Modeling Techniques III. Data Visualization Methods

I. Datasets

In this paper, following datasets were acquired with web scraping techniques from the standard and public websites.

a. COVID-19 cases dataset

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The COVID-19 Cases state (Ministry of Health and Family Welfare, n.d.) wise details are collected from the government of India's ministry of health and family welfare's website. The data on their website is updated on a daily basis.

b. Test Details (Numer of COVID-19 Tests)

The testing details (Coronavirus Outbreak in India, n.d.) are collected from www.covid19india.org. It's a crowdsourced initiative which collects all the relevant details about the virus in India. They use state bulletins and official handles to update their numbers. The data is validated by a group of volunteers and published into a Google sheet and an API. The API is available for all at api.covid19india.org for further analysis.

c. Mobility Trends

The Google mobility reports () track the movement of people across different states in India at locations like parks, grocery and pharmacy shops and workplaces. The data sets are completely anonymous and aggregated over the region and sub-regions under study.

The mobility trends for pharmacy and grocery gives information about the movement of people to places like grocery shops, market, drug stores. The transit trends give information about the movement of people to public transport hubs such as railway, metro stations and airports. The workplace trends give information about the visit of people to their workplaces. The residential trends will include the information about the stay at the place of residence

d. Population Density

The data for population density in Indian terrain is acquired with webscrapping of standard census site. The data available on Indian census site is till 2011. Hence the data presented for the survey is from the standard worldometer site which is an authentic source for the measures on demographics of all the countires in the globe.

II. Modeling Technique

Data wrangling and Data Preprocessing operations were performed before building OLS model. Data standardization were also informed on the dataset.

Ordinary Least square model was fitted for predicting the active cases and death rate with grocery and transit mobility trends. Ordinary least square model gives statistical information. The inferences are based on correlation co-efficient, R2, adjusted R2.

OLS was preferred because, it minimizes the residuals that is error between observed and predicted values.

OLS regression model works with pexplainatory variables Y as dependent variable, b0 as intercept and Xj as jth explainatory variable, e as random error is given by

$$Y = b0 + b1\ X1 + bnXn + e$$

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Scatter plots were used for capturing the correlation between active cases and mobility patterns. The correlation between deathrate and the mobility trends is also captured with the scatter plot

III. Data Visualization Methods

The data visualization methods are used for getting the insights about the active cases with the mobility patterns. The effect of residence, workplace, grocery and pharmacy mobility on the active cases were analyzed with the visualization methods. Comparative analysis of the mobility trends across the different states of India were observed with the visualization techniques.

4. RESULTS AND DISCUSSIONS

The results are presented in three ways.

1. Data Visualization for progession of active cases with the 3 mobility trends statewise.
2. Statistical data modeling for capturing the correlation between
   a. *Active cases* and *grocery & transit trends*
   b. *Death rate* and *grocery & transit trends*
3. Analysis of statewise population density and number of active cases.

I. Mobility Trends: Top 11 States

The analysis of the mobility trends is done by capturing the data for India after the lockdown was announced in March 2020 and is observed as the lockdown was extended in the second and third stage. The study is carried out in parts of time series. The candidate states were chosen for our study. The choice of the states was done on the basis of the effect of spread of COVID-19 till our study that is 10th May 2020. This period elucidates the degree of compliance of the lockdown phase 1, 2 and 3 in that state.

1) Kerala

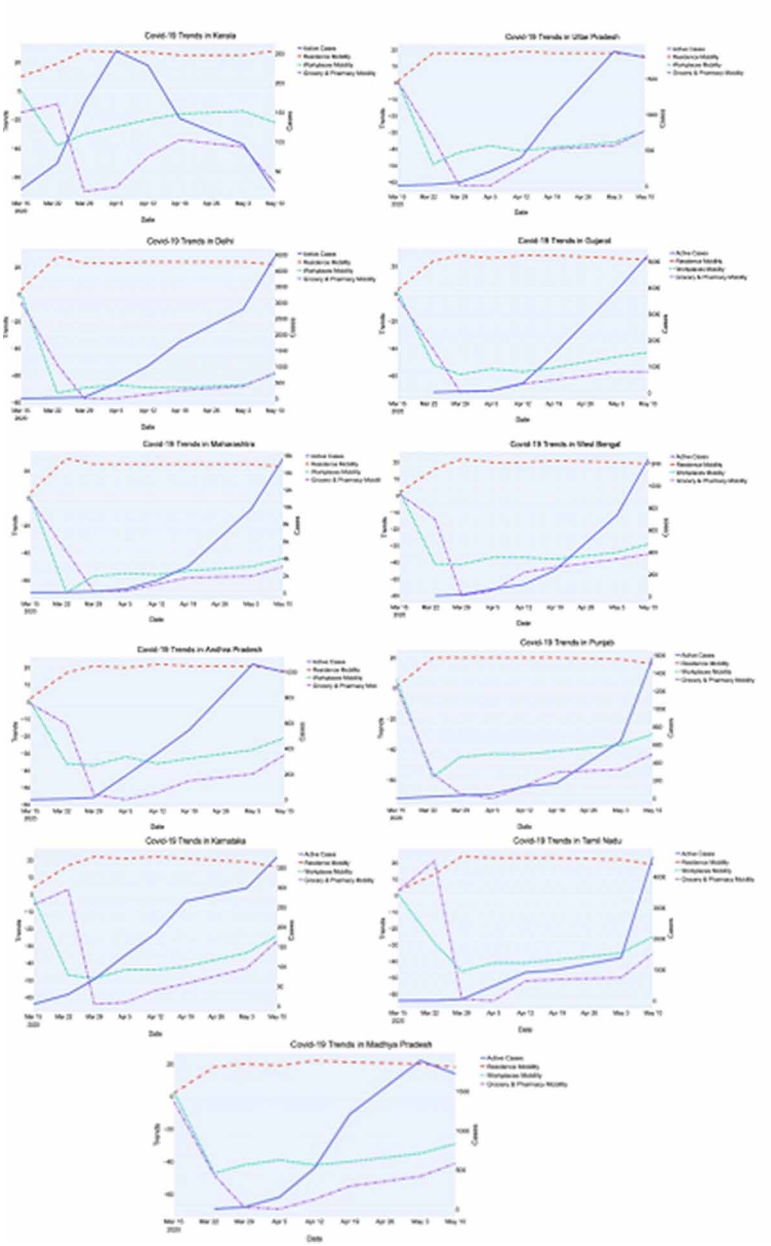
The state exhibits strict implementation of lockdown in the early days of lockdown. The figure 1shows a fall in residence mobility after lockdown phase 1 and the workplace mobility and grocery mobility looks to have risen coming back to normalcy. This implies the state moved to less restricted lockdown. However, this also may lead to a rise in the number of cases in the immediate future.

2) UttarPradesh

The strict adherence to lockdown is seen to be followed by the mobility trends from the month of March 2020. Figure shows there was stability or slower rise in active cases towards end of Lockdown phase 1 as the causal effect of adherence to strict lockdown, as the residence mobility was very high but as observed from the figure 1, workplace and grocery mobility is increased in the second phase of lockdown. The number of active cases also shows an increase.

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Figure 1. Mobility Trends across 11 states in India



3) Andhra Pradesh

The Figure shows a sudden increase in the residence mobility trends in the state at the beginning of lockdown phase 1. Although the workplace mobility has fallen after the lockdown, there looks a steady rise in it towards the extended lockdown. The Grocery and Pharmacy tends show a steady rise which means that the people have moved out for daily needs. The workplace mobility also shows an upward trend towards extended lockdown.

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4) Punjab

Both the residence and workplace mobility look to be in control, which has been seen with very few cases in the state at the earlier stage of lockdown. The Punjab government could successfully control the spread of the virus till lockdown 3.0 but the graph also shows the sudden spike in the number of active cases because of the interstate mobility and large number of people who travelled from Nanded in Maharashtra to Punjab () during lockdown 2.0.

5) Maharashtra

Maharashtra has the highest number of the active corona patients in the country. Graph shows steady rise in the number of active cases till the end of lockdown 1, as there was stability in residence and workplace mobility. The reason for sudden spike during Lockdown 2 is a large number of international travellers returned to their home country. Maharashtra holds the topmost thickly populated wards in Mumbai and the geospatial distribution shows that it has been responsible for the uncontrolled spread of this disease in Mumbai and Maharashtra. Population density helps to contribute towards the spread of the epidemic in Mumbai. The city has 43% of the total thickly populated wards all over the country. Analysis also shows that over 50% of the positive cases in the country fall in the wards which are over density of 35K persons per square kilometre.

6) Delhi

In Delhi, the implementation of lockdown was followed strictly. There was a complete lockdown with respect to interstate mobility. The interstate mobility however restarted during lockdown 3 and thereafter a sudden spike in the active number of cases, is seen in the graph.

7) Tamil Nadu

Tamil Nadu is another state after Maharashtra, where a large number of active cases are seen. Tamil Nadu shows a compliance between the residence and workplace trends in the lockdown period. The relaxed mobility during lockdown phase 3 with respect to grocery and pharma and transit trends is seen and can be correlated to rise in the number of cases in the state.

8) Madhya Pradesh

As the Figure shows the increase in active number of cases at the end of Lockdown 1. The graph also shows an increase in grocery and pharmacy mobility trend and this also leads to an increase in total number of cases.

9) Karnataka

The early closure of schools, colleges, offices helped them to control the number of cases. But as there was relaxation in rules during lockdown 3, there is change in mobility and pharmacy trends and a consequent increase in the total number of active cases.

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10) West Bengal

In West Bengal, readers can see that they were less restrictive lockdown. They followed a relaxed policy of "humane lockdown". The intercity transport was running in different districts across the state where there was no record of COVID-19 cases. The mobility trend of grocery and pharmacy can also be observed from the graph which perhaps show rise in number of cases.

11) Gujarat

Gujarat also seems to be adhering to the lockdown constraints very strictly. But the densely populated areas in Gujarat are supposed to be the reasons for its widespread and uncontrolled behaviour. The rise in the cases is seen more during lockdown 2 and interstate mobility is recorded in March from Delhi to Gujrat. State of Gujarat has three of the cities that account for more than 50% of the thickly populated wards

II. Comparative Analysis of the Mobility Trends Across the Different States of India

Figure 2. COVID-19 Workplace Trends for different states



A) Workplace Trends

From figure 2, it is seen that in Kerala, higher trends in workplace mobility were observed in lockdown 1.0, 2.0, 3.0 as compared to all other states. After Kerala, the higher movement of people is observed to workplaces in Uttar Pradesh and Gujarat respectively. However, in Delhi very lesser movement to workplaces were observed during lockdown 1.0, 2.0, 3.0.

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B) Grocery and Pharmacy Trends

Figure 3. COVID-19 Grocery and Pharmacy Trends for different states



From Figure 3, it can be seen that the highest number of Grocery and Pharmacy mobility trends were observed in the Kerala. During lockdown 1.0, 2.0, 3.0. Uttar Pradesh has slightly lesser grocery and Pharmacy mobility trends as compared to Kerala. However, there was a very lesser movement of people to grocery and pharmacy shop is observed in Delhi.

C) Transit Trends

Figure 4. COVID-19 Transit Trends for different states



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From figure 4, it is seen that the higher transit trends were observed in Kerala during lockdown 1.0, 2.0, 3.0. However, in Delhi people preferred to stay at home and hence observed a fall in the transit trends during lockdown 1.0, 2.0, 3.0.

III. Regression Analysis and Mobility Trends: Statistical data modeling for correlation

The data for analysis is extracted from Google Mobility Report (). The statistical model is built with OLS (Ordinary Least Squares). Grocery Pharmacy is considered as Independent variable and Active cases are considered to be dependent variable.

It is found, there is high positive correlation between Grocery Pharmacy mobility trend and active number of cases for Uttar Pradesh, Delhi and Gujarat. It shows that the Grocery Pharmacy mobility trend has drastically affected the number of active cases. The people in these cities have not changed their shopping patterns during the lockdown.

Table 1. Regression Analysis for 5 states, Grocery Pharmacy Mobility trend as Independent variable and Active cases as Dependent Variable.

	Maharashtra	**Gujarat**	**Tamil Nadu**	**Uttar Pradesh**	**Delhi**
Active Cases	**Google Mobility Reports**				
Grocery Pharmacy Mobility	468.6474	209.7577	62.1595	46.3292	157.4728
R-Squared	0.69	0.75	0.62	0.79	0.77
Adjusted R-Squared	0.68	0.74	0.61	0.78	0.77

Transit mobility is considered as an Independent variable and Active cases are considered to be dependent variable. The high positive correlation is observed between the transit mobility trends and active cases in Delhi and Maharashtra. The transit mobility has vastly affected the number of active cases in both the states.

Delhi and Maharashtra show that there is higher impact of transit mobility on the number of active cases in the respective region.

Table 2. Regression Analysis for 5 states, Transit Mobility trend as Independent variable and Active cases as Dependent Variable

	Maharashtra	**Gujarat**	**Tamil Nadu**	**Uttar Pradesh**	**Delhi**
Active Cases	**Google Mobility Reports**				
Transit Mobility	1150.3494	327.93	133.4817	157.8676	339.341
R-Squared	0.79	0.74	0.74	0.65	0.84
Adjusted R-Squared	0.79	0.74	0.74	0.64	0.83

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Table 3. Regression Analysis for 5 states, Grocery Pharmacy Mobility trend as Independent variable and Death as Dependent Variable

	Maharashtra	Gujarat	Tamil Nadu	Uttar Pradesh	Delhi
Death	**Google Mobility Reports**				
Grocery Pharmacy Mobility	24.0623	15.3569	0.7587	1.2905	231.9144
R-Squared	0.73	0.69	0.57	0.73	0.61
Adjusted R-Squared	0.72	0.68	0.56	0.72	0.60

High positive correlation is seen with Grocery Pharmacy mobility and the number of deaths in a state. Grocery Pharmacy mobility influenced the number of deaths in Maharashtra and UP. Similarly transit mobility in Maharashtra and UP show an impact on the death rate due to Covid-19 as shown in Table 4.

Table 4. Regression Analysis for 5 states, Transit Mobility trend as Independent variable and Death as Dependent Variable

	Maharashtra	Gujarat	Tamil Nadu	Uttar Pradesh	Delhi
Death	**Google Mobility Reports**				
Transit Mobility	58.3573	23.6148	1.6463	5.1029	555.6873
R-Squared	0.82	0.66	0.70	0.81	0.66
Adjusted R-Squared	0.81	0.66	0.69	0.81	0.65

IV. Number of Tests Conducted

Figure 5 shows, Maharashtra is the only state where the largest number of tests have been conducted as compared to all other states in India and has also got highest number of active cases. Tamil Nadu, Andhra Pradesh and Kerala carry out larger number of tests.

Graph also shows states like Gujarat; West Bengal carry out very few tests which may lead in less discovered cases.

V. Active Cases and Death Rate

A) Active Cases vs Grocery and Pharmacy Trends and Transit Trends

It is found that grocery and pharmacy trends are highly impactful on the active cases in the state of Delhi and Uttar Pradesh. The transit trends are highly correlated with number of active cases in the states of Delhi and Maharashtra. This in turn gives an insight that the states should be enforcing transit restrictions in the later stages of lockdown.

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Figure 5. Positive Tested Samples in Various States

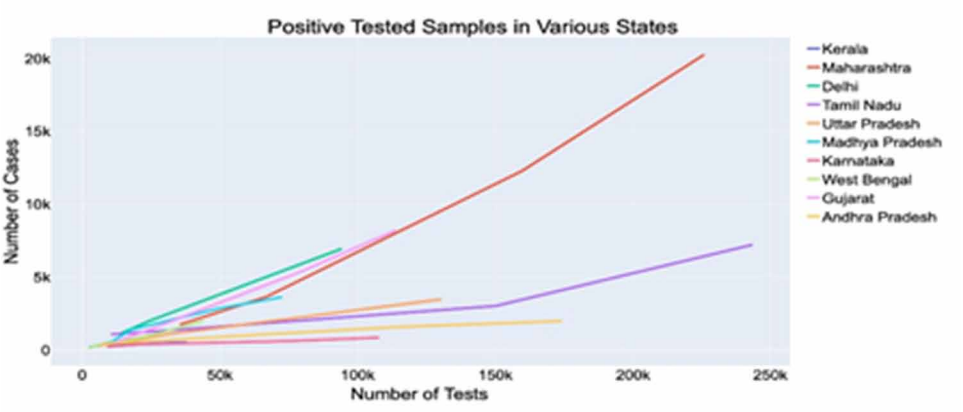
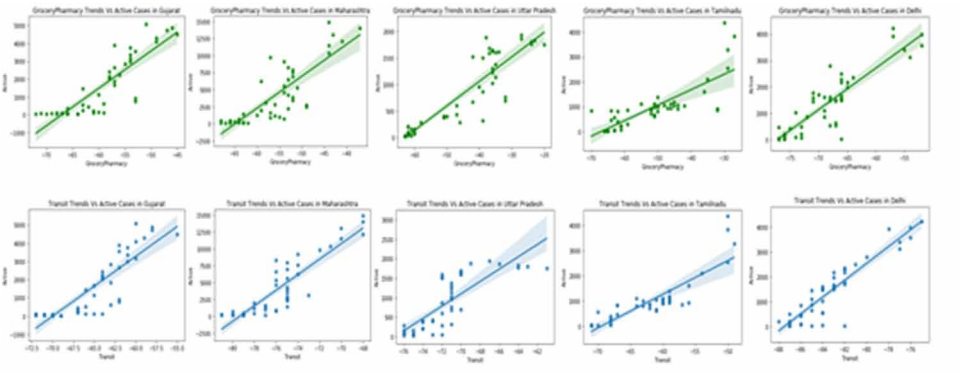


Figure 6. Active Cases vs Grocery & Pharmacy Trends and Transit Trends



B) Deaths vs Grocery and Pharmacy Trends and Transit Trends

It is found there is high correlation between Transit mobility and the number of deaths. From these plots, it can be concluded that the transit mobility in Uttar Pradesh and Maharashtra has majorly affected the number of deaths.

VI. Population Density Analysis

The bar chart shows the population density of the major cities in the most affected states of India. Population density is seen to contribute towards the contact rate and thereby spread of the disease. This gives insight that the states with higher population density should enforce stricter mobility constraints even during later stages of lockdown.

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Figure 7 Deaths Vs Grocery & Pharmacy Trends and Transit Trends

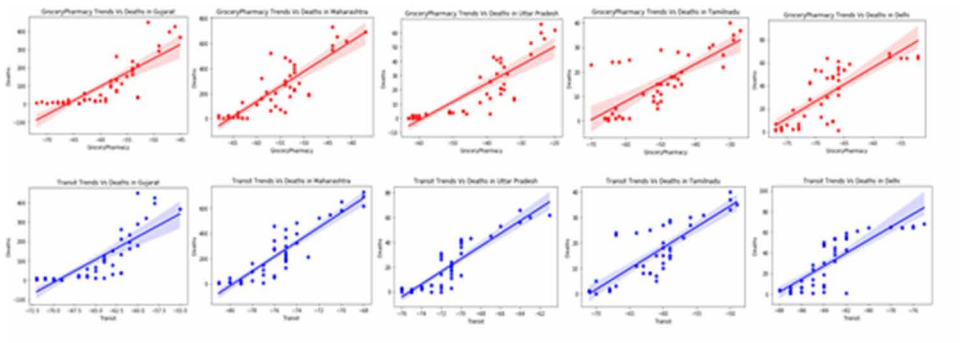
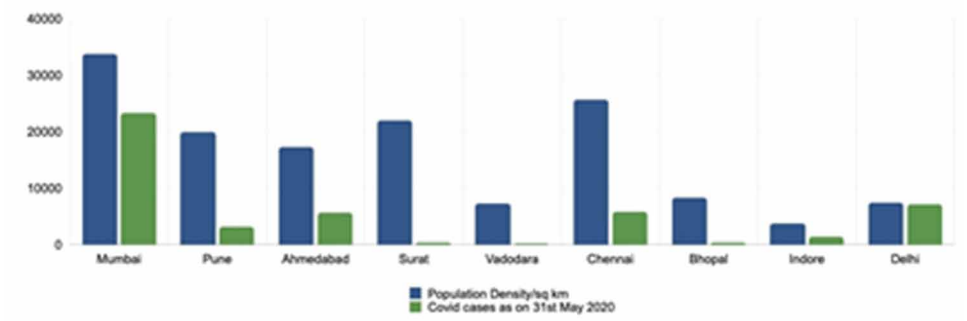


Figure 8. Population Density of major cities in the most affected states



5 CONCLUSION

In this work, authors analysed the effect of human mobility trends on the spread of COVID-19 across different states in India. Various mobility trends such as workplace, residential, grocery store as an effect of lockdown 1.0, 2.0, 3.0 are studied and how it affected the number of active cases and death rate in different states in India. Authors have also statistically analysed the grocery and pharmacy mobility and transit mobility trends for 5 different majorly affected states in India to understand the effect of lockdown 1.0, 2.0, 3.0 and its correlation to the number of active cases and death rate.

The work highlights the performance of the number of tests conducted and the detection of active cases and the population density of the cities towards the spread of the disease. The proposed work shows higher correlation between mobility trends and the number of active COVID-19 cases with death rate in few states of the country. This trend analysis will be helpful to constrain human mobility and its impact on COVID-19 cases in particular regions of India. The study will be helpful to the government and public health authorities to take actions to control the spread of pandemic COVID-19 especially in thickly populated regions. This gives insight that the states with higher number of active cases should enforce stricter mobility constraints even during later stages of lockdown.

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Chapter 15
M2UNet++: A Modified Multi-Scale UNet++ Architecture for Automatic Liver Segmentation From Computed Tomography Images

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ABSTRACT

Liver segmentation is instrumental for decision making in the medical realm for the diagnosis and treatment planning of hepatic diseases. However, the manual segmentation of the hundreds of CT images is tedious for medical experts. Thus, it hampers the segmentation accuracy and is reliant on opinion of the operator. This chapter presents the deep learning-based modified multi-scale UNet++ (M2UNet++) approach for automatic liver segmentation. The multi-scale features were modified channel-wise using adaptive feature recalibration to improve the representation of the high-level semantic information of the skip pathways and improved the segmentation performance with fewer computational overheads. The experimental results proved the model's efficacy on the publicly available 3DIRCADb dataset, which offers significant complexity and variations. The model's dice coefficient value is 97.28% that is 7.64%, and 2.24% improved from the UNet and UNet++ model. The quantitative result analysis shows that the M2UNet++ model outperforms the state-of-the-art methods proposed for liver segmentation.

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INTRODUCTION

Healthcare is one of the high-priority sectors where people presume the utmost care and services. In the healthcare sector, due to technological advancement, disease diagnosis and clinical procedures have become technology-driven. In diagnostic radiology, medical imaging is the fundamental tool for the analysis and interpretation of diseases using medical images. Medical imaging is the non-invasive technique to visualize the body organs and tissues' internal anatomy, which allows the medical expert to diagnose the disease, decide the treatment planning, and post-treatment assessment (Razzak et al., 2018). The radiological images are acquired using acquisition devices that produce digital images of internal body parts and tissues in different imaging modalities. The commonly exploited image modalities are X-ray, Ultrasound, Computed Tomography (CT), Magnetic Resonance Imaging (MRI) by medical experts. Recently, medical data became more prominent due to advanced medical image acquisition devices capturing high-resolution radio images with many slices per scan to represent the internal structure in 3D that increases volume and storage requirements of the medial images (Hesamian et al., 2019). However, the analysis and interpretation of the large volume of medical images are challenging for the medical experts to reach the correct decision in less time. In making the process automated through computer vision algorithms, many researchers developed interactive and automatic methods for analyzing and interpreting medical images that enable the medical experts to reach the correct decision faster.

BACKGROUND

The liver is one of the highly critical and largest human body organs. It accomplishes the major functionality of detoxification and supplying fluids to the body parts. Automatic liver segmentation has been decisive in medical explication and therapy framing for hepatic complications such as liver transplantation, hepatectomy, treatment of the liver tumor for the targeted therapies (radioembolization), post-treatment assessment, and also beneficial for the progress of the computer-aided diagnosis (CAD) framework for hepatic disease diagnosis (Bilic et al., 2019) (Moghbel et al., 2018). In clinical routine, the radiologist or physician delineate the liver manually slice by slice manner. However, the liver's manual outline is time-consuming and tedious because the availability of the abundant medical data volume that leads the segmentation depends on the expert because of its inconsistency, human limitations, and intricacy of the data. Because of these reasons, investigators in the domain focusing on the separation of the liver automatically. For hepatic diseases, CT images are widely used for clinical diagnosis due to their sturdiness, broad accessibility, speedy capturing procedure, and superior resolution (Gotra et al., 2017) (Domingues et al., 2020). In literature, to foster the medical field's demand, several frameworks are proposed for the automatic liver segmentation from CT volume without human intervention that becomes the second opinion for the medical experts to make the correct decision in less time. However, it remains challenging due to liver size variation, fuzzy liver boundaries, and Intensity similarity between the liver and adjacent organs. The liver is a delicate tissue, and its structure is extremely reliant on its adjacent organs.Typically, liver images are obtained by injecting a contrast agent to improve the liver area in CT images while capturing. However, acquiring CT images is a noisy process without contrast enhancement. The contrast enhancement further introduces noise in the CT scan images, and its injection phase decides the amount of noise in the acquired CT images (Moghbel et al., 2018). Because of the above complications, it remains a challenging task.

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RELATED WORK

Various methods have been proposed to segment the liver automatically from abdomen CT scan images in literature. The conventional automatic liver separation approaches built on the dissemination of the Hounsfield Units (HU) values in CT slices utilized to represent the features, shape information, and texture of the liver portion was classified into three categories constructed on a gray level, structure, and texture (Luo et al., 2014). However, these models' performance was limited because the model parameters were decided based upon the expert's prior knowledge, which is significantly affected by expert to expert.

Afterwards, the various machine learning algorithms were proposed with the help of the neural network, clustering mechanism, and statistical modelling. Finally, it was utilized to design the computer-aided diagnosis (CAD) framework for the medical experts (Moghbel et al., 2018) to delineate liver and tumor.

From the last decade, deep learning models maturing continuously in many application areas. In medical imaging, deep learning-based CNN architectures achieved expert-level performance in various medical applications, including disease classification, organ segmentation, lesion detection, tumor classification, diabetic retinopathy screening (Chea & Mandell, 2020). Deep learning algorithms, in specific CNN, have become a technique for examining medical images for various applications that are summarized (Litjens et al., 2017). Deep learning is a subgroup of artificial intelligence is an emerging field that incorporates widespread neural network architectures devised to carry out a variety of tasks (Yamashita et al., 2018). Deep learning frameworks have proven their effectiveness in many computer vision applications compared to the traditional machine learning approach (Greenspan et al., 2018). The most established deep learning model utilized for the images is CNN. It has been a leading technique in computer vision tasks due to its robust nonlinear feature abstraction potential by exploiting several filters at various network layers and its competence to manipulate a massive data volume (Suzuki, 2017). The CNN-based architecture delivered an astonishing performance in the ImageNet Large Scale Visual Recognition Competition (ILSVRC) (2012) (Ueda et al., 2019). The researchers employed CNN-based architectures in the clinical realm and demonstrated their effectiveness. The medical image segmentation frameworks and the future challenges were explained with reference to the most recent like 2D and 3D UNet, V-net, Convolutional Residual Networks (CRNs), Recurrent Neural Networks (RNNs), and deeply supervised network training approach discussed (Hesamian et al., 2019). The importance of various deep learning algorithms for medical image segmentation includes supervised and weakly supervised network details, and design aspects based on the learning mechanism reviewed thoroughly (Lopez-Linares Roman et al., 2020). Lately, the UNet derived ANU-Net was utilized for the medical image separation by modifying the high-level features with a nested attention mechanism (C. Li et al., 2020). The medical domain researchers attempt to develop CNN-based innovative techniques for backing the researchers and transforming the radiologist and medical experts' routine practices.

Recent Trends in Automatic Liver Segmentation

Liver segmentation using an abdominal CT scan is a process of extracting the liver region from the images. Recently, deep CNN became the choice of many researchers to segment liver parenchyma automatically from CT images. The CNN-based fully convolutional neural network (FCN) with encoder-decoder is employed to segmentation the liver from the medical images. The FCN based UNet architecture proposed for biomedical image processing (Ronneberger et al., 2015) become the decision for several FCN based architectures utilized for image segmentation. Afterwards, UNet derived methods were proposed

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for medical image analysis. In Liver Tumor Segmentation Benchmark (LiTS) challenge (2017), the majority of approaches proposed were derived from baseline UNet. Nearly all the approaches exploited explicit preprocessing on the input data, and few have applied postprocessing to refine the segmentation outcomes further (Bilic et al., 2019). The UNet extensions were proposed to analyze the interslice and intra slice features using hybrid features fusion layer and dense network for liver and tumor delineation (X. Li et al., 2018). The 3D liver and tumor extraction approach was proposed based on residual learning with the abstraction of multi-scale information and accumulation by accumulating high-level and low-level features (Jin et al., 2018). The deep belief network was recently proposed with unsupervised pretraining and fine-tuning by the supervised approach for pixel-by-pixel feature learning and refined the result by an automatic active contour algorithm (Ahmad et al., 2019). The segmentation performance of UNet was uplifted by modifying the high-level features in the skip connection by fusing the object-dependent filtering features with high-level features (Seo et al., 2020). The comparative analysis FCN based architecture, including SegNet, UNet, Dense UNet, and ResUNet were presented for automatic liver delineation. This study intends to incorporate automatic liver segmentation into the commercial software LiverVision (Sengun et al., 2021). The DFS-UNet proposed to uplift the liver segmentation performance by modifying the skip-connections with dense feature selection mechanisms to tackle the segmentation difficulties like small liver regions and discontinue liver boundaries (Liu et al., 2021). The UNet inspired SAR- U-Net was proposed that exploited the Squeeze-and-Excitation network for optimization of high-level features in the skip connection and multi-scale Atrous Spatial Pyramid Pooling (ASPP) module employed for better representation of sematic details in the bottleneck layer of the network to upgrade the automatic liver segmentation performance (Wang et al., 2021). The UNet based architecture has gained significant attention from the research community for automatic liver segmentation.

Limitations of UNet Architecture

The UNet is FCN encoder-decoder-based design that becomes the choice for segmentation. It has an encoding (contraction) path that characterizes the features of an input image, and a decoder has been designed to rebuild the segmentation result. The encoding path downsamples the features that comprise consecutive convolution layers and max-pooling layers, thus shrinking the features. The encoding process extracts high-level features, and low-resolution features pass to the successive encoding stages. The decoding path rebuilds the low-resolution features using upsampling operation. The decoding path result is the segmented feature maps with the input image size (Seo et al., 2020).

The UNet performance is limited due to substantial loss of spatial contents from input images. This loss occurs due to consecutive downsampling by pooling and convolution operations at each encoding stage of UNet. Hence, the feature size becomes reduced, and high-resolution features of the object are extracted at each stage, and the network learns the details about the object in the input image. The number of encoding stages increases the network to learn more information about the object. However, introducing additional encoding stages will not ensure better segmentation performance because of contextual information loss. As a result, the network lost the object's location details of an input image. The contextual information about the object cannot be propagated to the deeper layers as the number of layers increased. Thus, the network lost spatial contents, which cannot be recovered entirely in upsampling stages. In medical image segmentation, contextual contents have a critical role in the accurate analysis of the interested region. Therefore, the performance of the UNet is limited up to a certain level.

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Multi-Scale Approach in CNN

CNN characterizes the significant features and efficiently estimates the target object's coarse edges in the image for semantic segmentation. However, the encoder output feature size is notably reduced; thus, it obstructs the accuracy of CNN. Therefore, to improve the segmentation performance, it is essential to derive the object's explicit contextual contents by processing the features at various scales to achieve better segmentation performance. The feature multiscaling is attained in the encoder-decoder network by accumulating the low-level and high-level features from the deeper stages with preceding stages to capture the local and details of the object. Hence the multi-scale approaches reached efficient semantic segmentation outcomes.

This chapter presented the modified multi-scale UNet++ (M2UNet++) architecture to refine the liver segmentation performance by adaptively recalibrating multi-scale features channel-wise from CT images.

METHODOLOGY

In this chapter, the authors proposed a CNN-based modified multi-scale UNet++ network for liver segmentation. The proposed architecture is the extension of UNet++ architecture (Zhou et al., 2018) (Zhou et al., 2020). UNet++ network comprises nested UNets whose encoders and densely connected decoders with identical resolution feature maps through the restructured skip connections. The deep supervision employed allows the aggregation of output from the different depths that enables the model pruning. The skip pathways are modified in the UNet++ to extract the multi-scale features better to represent high-level features and restored the semantic difference in encoding and decoding convolutional layers. The dense connections are utilized to fuse features from the different convolutional layers of different stages and explicit representation of multi-scale features. The dense connection extracts the semantic information from the different layers and fuses at the intermediate nested convolutional layers. The low-resolution feature maps are fused with the high-resolution features to represent the object's semantic information in the input features.

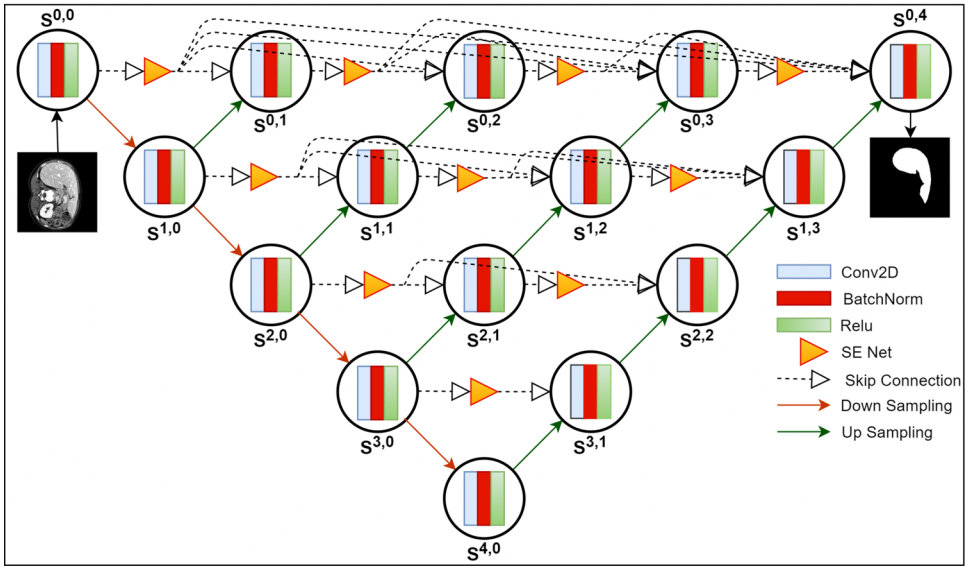
The authors proposed the modified multi-scale UNet++ architecture to improve the liver segmentation performance by modifying the skip pathways of UNet++ architecture. The proposed design innovation is that the skip pathways and nested convolution layer features are modified channel-wise using the channel attention by Squeeze-and-Excitation Network (SENet), as shown in Figure 1. Then, the convolutional layer's output features are concatenated with the SENet output representing the semantic features prominently at each nested stage. Thus, the network learns the prominent high-level features of the object.

The proposed model introduced channel-wise feature remapping to improve the semantic features in the nested layers of the UNet++ architecture. The channel-wise feature recalibration was achieved using the SENet (Hu et al., 2018), as shown in Figure 2. It modifies the aggregated multi-scale features into the prominent channel-wise modified features in two-step operations called squeeze and excitation.

In squeeze operation, the SENet converts the input features into 1-dimensional features using a global pooling operation, and the size is equivalent to the input feature channels. Thus, in the squeezing step, the global information of the input features is captured. It is defined as follows (Eq.1),

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Figure 1. Proposed multi-scale modified UNet++ architecture.



$$V_C = F_{sqe}\left(X_C\right) = \frac{1}{H \times W}\sum_{i=1}^{H}\sum_{j=1}^{W} X_C\left(i,j\right) \tag{1}$$

Where X_C is one of the channels of input features $X = [X_1, X_2, X_3, \ldots, X_C]$, V_C – is one of the transformed channels from the vector $V = [V_1, V_2, V_3, \ldots, V_C]$ that adopts the expressive data of input feature maps. The size of the input feature maps is $H \times W \times C$.

In excitation operation, the 1-dimensional input vector is isolated channel-wise and transformed through the simple gating mechanism with two fully connected (FC) layers with nonlinear relu δ and sigmoid σ activation to improve the generalization capability. The operation expressed as (Eq.2),

$$E = F_{Ex}\left(V, W\right) = \sigma(g\left(V, W\right) = \sigma\left(W_2\delta\left(W_1 V\right)\right) \tag{2}$$

Where $W_1 \in \mathbb{R}^{\frac{C}{r} \times C}$ related to first FC and $W_2 \in \mathbb{R}^{C \times \frac{C}{r}}$ related to second FC and r- controls the required computation and dimensionality of the FC layers. The authors employed r=8 that illustrates the satisfactory performance for the medical image segmentation (Rundo et al., 2019) (Kushnure & Talbar, 2021). In this step, the input features are adaptively modelled or recalibrated channel-wise. At last, the scaling operation performed to obtain the renovated features that offer more attention to the essential details of the input features represented as (Eq.3),

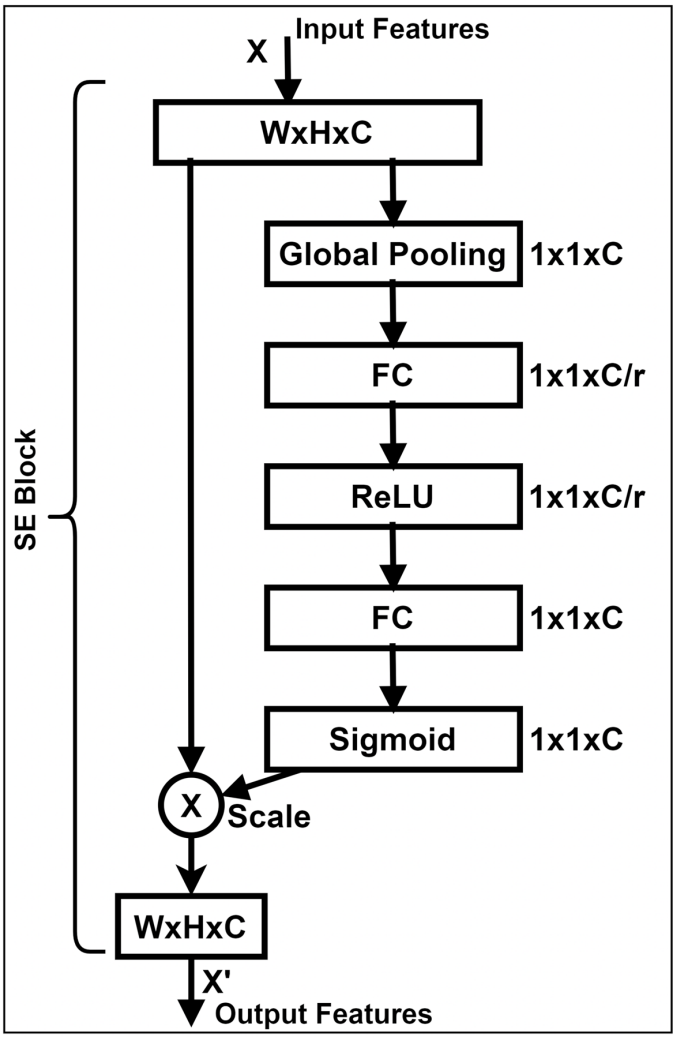
$$SE_C\left(X_C\right) = \tilde{X}_C = F_{scale}\left(X_C, E_C\right) = X_C E_C \tag{3}$$

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Where $\tilde{X} = \left[\tilde{X}_1, \tilde{X}_2, \tilde{X}_3, \ldots, \tilde{X}_C \right]$ and scaling operation $F_{scale}(X_C, E_C)$ input features multiplied channel-by-channel with the $E_C \hat{I}[0,1]$, $X_C \in \mathbb{R}^{H \times W}$ and $SE(X)$ the channel-wise adaptive recalibrated features of the input features. Hence, the scaling output is the recalibrated features having equivalent channels. However, the feature maps represent the key details more prominently, which results in a better representation of high-level semantic information at nested convolutional layers.

The modified multi-scale UNet++ improves the channel interdependencies of each nested convolution layer's output feature maps without a heavy computational burden on the existing architecture. The purpose of feature recalibration of each convolution layer's output is to focus more on the relevant features from the accumulated multi-scale feature maps that boost the successive layers learning ability and network segmentation performance.

Figure 2. Squeeze-and-Excitation Network utilized in the proposed architecture.



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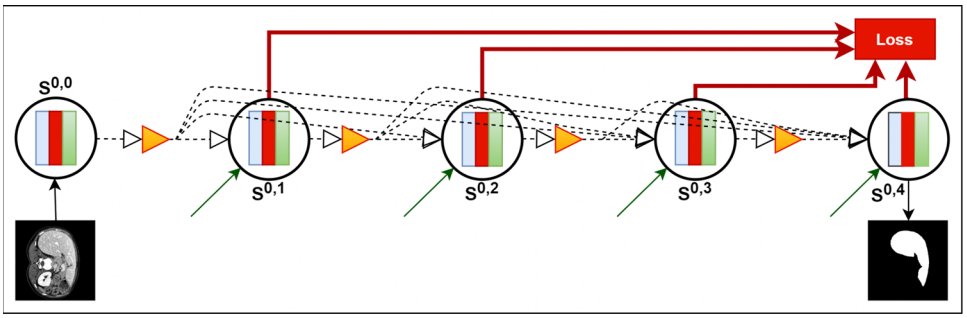
The multi-scale features extracted by the encoder stages and nested layers of the network along with the modified multi-scale features by SENet to represent rich semantic details at each stage of the network is expressed as follows as (Eq.4),

$$s^{i,j} = \begin{cases} \mathbb{C}\left(M\left(s^{i-1,j}\right)\right), & j = 0 \\ \mathbb{C}\left(\left[\left[SE\left(s^{i,k}\right)\right]_{k=0}^{j-1}, \mathcal{F}\left(s^{i+1,j-1}\right)\right]\right), & j > 0 \end{cases} \tag{4}$$

Where $s^{i,j}$ - is represented output of each network node, *i* and *j*- are the encoder downsampling layer index and dense block convolution layer of the skip connection, respectively. The $\mathbb{C}(.)$ - is the convolution, batch normalization, and relu activation, $\mathcal{M}(.)$ - is max-pooling operation, $\mathcal{F}(.)$ - upsampling, and [ ] - indicate the concatenation action.

In the UNet++ model (Zhou et al., 2020), deep supervision allows the model pruning. As a result, it substantially reduced parameters as well as the prediction time of the model. However, model pruning degrades the performance because loss varies at different stages considered for the prediction. Therefore, we have not utilized deep supervision while training the model. However, it is feasible to employ deep supervision with the proposed network. The deep supervision of the model loss is observed at the different nested UNet stages while prediction nested UNet stages are utilized, as shown in Figure 3.

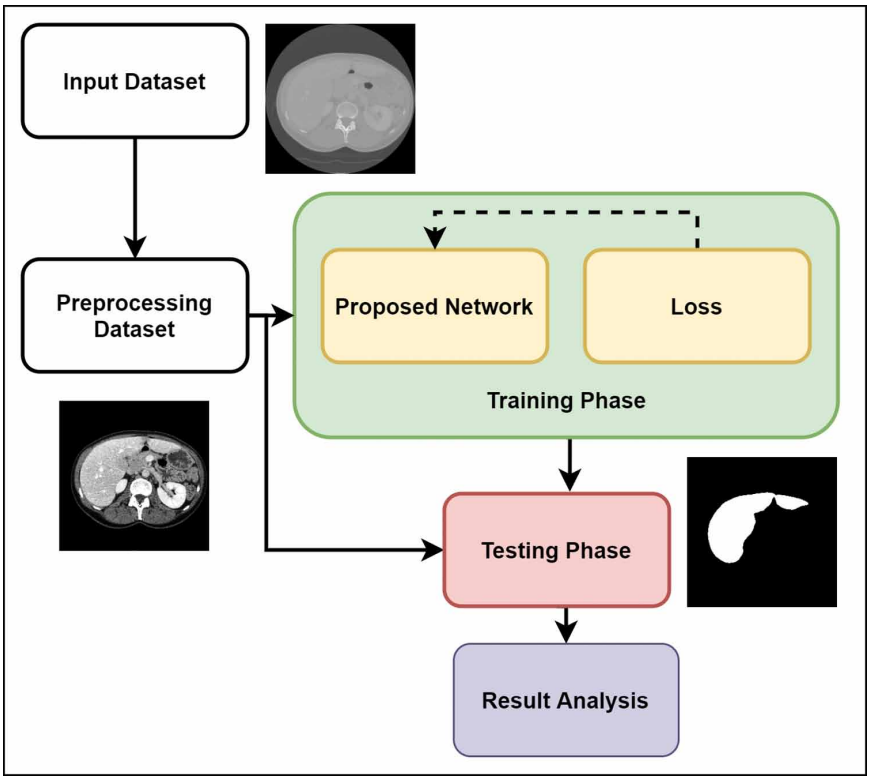
Figure 3. Modified multi-scale UNet++ architecture with deep supervision.



The deep learning models work in two phases called the training and testing phase. Figure 4 indicates the training and testing flow of the model. The dataset utilized for training and testing is preprocessed first. Then, the network is trained on the training dataset, which optimizes network weights based on training loss. Finally, input preprocessed CT images were tested in the testing phase, and the network obtained the segmented map. Then, the network performance was decided using the different statistical measures.

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Figure 4. Modified multi-scale UNet++ training and testing pipeline



EXPERIMENTAL SETTINGS AND RESULT ANALYSIS

Dataset

The 3D Image Reconstruction for Comparison of Algorithm Database (3DIRCADb) (3Dircadb, n.d.) was utilized for the experimentation to verify the performance of the model. The 3DIRCADb database is available publicly, which comprises anonymous CT volumes of various patients and various structures of interest manually annotated by expert radiologists. A dataset containing the 20 3D CT volumes (10 men and 10 women) was acquired in an enhanced venous phase from several European hospitals through various CT image scanners. The spatial resolution is 512×512 for each axial slice. The dataset has three different annotated classes, which include liver, tumor, and background. For liver segmentation experimentation, the authors considered the liver a positive class, and all other classes are negative.

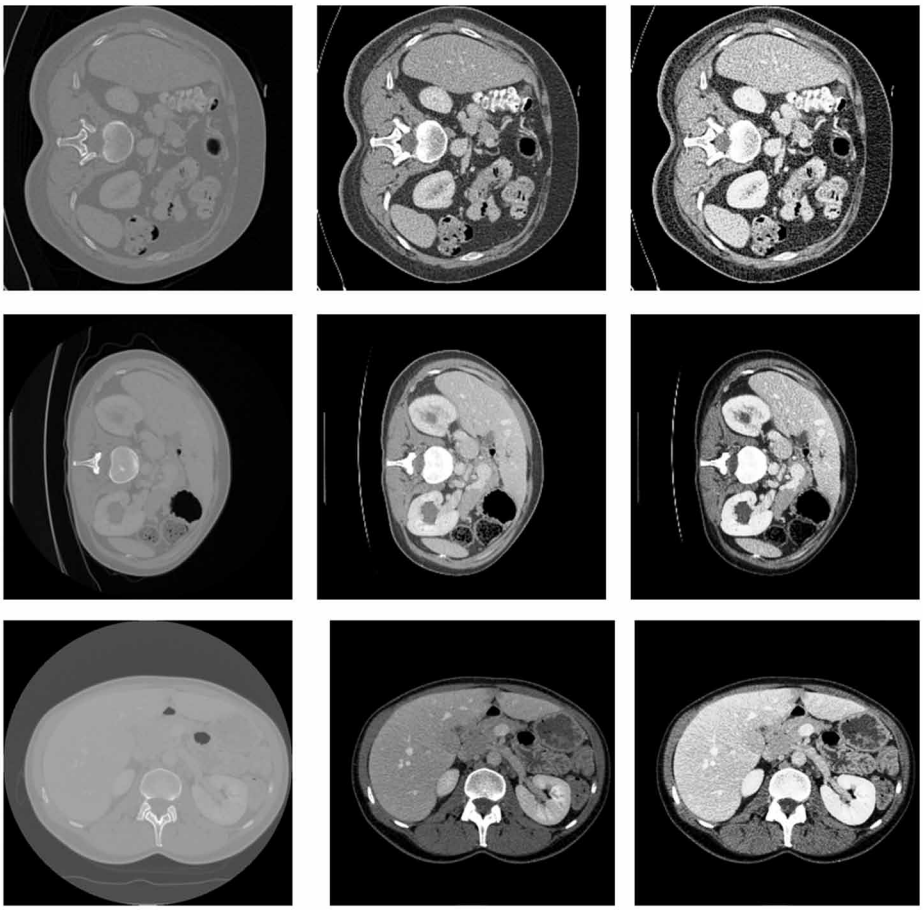
Dataset Preprocessing

The main objective is to outline liver parenchyma in the CT images. The abdomen CT images have other organs, and that hampers the segmentation accuracy. For achieving better accuracy, the immaterial details and organs were clipped from the data volume. The HU values represent the relative densities of different body organs in CT volume, ranging from -1000 to 1000. The densities for the liver tissue vary from 40 to 50 HU in CT Volume (Jin et al., 2018). To acquire a clean liver section for the processing, unwanted

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details from the CT volume were suppressed by preprocessing the dataset. The simple preprocessing steps followed by the authors include (a) resizing the dataset into 256×256 slice-by-slice for reducing computational burden, (b) global windowing of the CT volume with window size (-250, 200) HU so that the liver region is represented explicitly for the separation, (c) normalize the entire data on the same scale [0,1] that streamlines the training process; as a result, the network converges faster. In addition, image enhancement was applied to enhance the liver region in CT images. These preprocessing steps provide the clean liver region for processing. The preprocessing outcomes are illustrated in Figure 5.

Figure 5. Preprocessing results in the 1st column implies the resized (256×256) input images, the 2nd column implies the HU Windowing result, and the 3rd column implies the image enhancement result.



Training Configuration

The proposed network is trained from scratch using the network configuration shown in Table 1. The network initialized with learning rate (LR) $1\times e^{-3}$, during training, on plateau learning rate reduced with the patience of 5 epochs. The Weight decay regularization is used with the regularization factor $1\times e^{-3}$ to control the updates in the network parameters that minimize overfitting risk and improve the gener-

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alization capability. An enormous data volume is required for training a deep CNN network (Razzak et al., 2018) (Greenspan et al., 2018) to avoid overfitting and refining generalization performance. In the medical field, a large quantity of annotated data is a limitation for researchers in deep learning. Therefore, data augmentation is the means to scale up the dataset by employing the different image transformations on the input dataset. Data augmentation was achieved using the affine transformation (Hesamian et al., 2019) and Elastic deformation (Simard et al., 2003).

Table 1. Model training parameters with value

Network_Parameters	Setup_values
Starting LR	$1\times e^{-3}$
Smallest LR	$1\times e^{-10}$
Network optimizer	Adam
Regularization (L2)	$1\times e^{-3}$
Network loss	Binary dice loss
Training batch size	8
SE Net complexity (r)	8

Implementation Platform

The network is designed using the TensorFlow (Abadi et al., 2016) platform and high-level Keras API for artificial neural networks (Chollet, 2015). The terminal utilized for the implementation has the following configuration: Processor Intel(R)Xeon(R) CPU E5-16200 with 3.60GHZ, Memory 16 GB, graphics card (GPU) NVIDIA GEFORCE TITAN-X with memory 12 GB and operating system: Windows 10.

Evaluation Metrics

The overlap-based and similarity-based evaluation metrics were utilized to assess the proposed model's segmentation performance. The Dice Coefficient (DC), Intersection of Union (IoU), Volumetric Overlap Error (VOE), and Relative Absolute Volume Difference (RAVD) are based on the volume overlap and relative size between ground truth (GT) and the segmented result (Heimann et al., 2009). In addition, the volume similarity measures precision and recall utilized to signify the segmented map and ground truth similarities (Yeghiazaryan et al., 2015). These are the commonly exploited measures to evaluate the quality of segmentation results.

Result Analysis and Discussion

The performance analyzed using the metrics commonly utilized for the liver segmentation performance measurement are mentioned in the above section. The experiments were performed on the publicly available 3DIRCADb dataset, which offers significant complexity and variations in the dataset. The DC is the most preferred volume overlap measure utilized in evaluating the segmentation performance. The proposed model has shown considerable improvement in the DC compared to UNet (Ronneberger

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et al., 2015) and UNet++ architecture (Zhou et al., 2020). The DC for the proposed model is 97.28%, which is 7.64% and 2.24% better than UNet and UNet++ models. The precision and recall indicate the similarity in the segmented result and GT. The proposed model's precision value is 0.981 and recall value is 0.992, which shows the proposed model can classify the voxels accurately than the other methods. The quantitative analysis presented in Table 2 shows that the presented model outperforms compared with the other models. The multi-scale recalibrated features in the UNet++ skip pathways improve the semantic representation of the high-resolution information and preserve the region of interest by modelling features channel-wise. The segmentation results visualized in Figure 6 depict the difference in the segmentation outcome of the M2UNet++ and other methods. The proposed model has the capability to segment the convoluted liver parenchyma with minimum voxel classification error. The proposed model segments the complicated liver parenchyma from adjacent organs having feeble boundaries. The segmented output preserves the complicated liver parenchyma that reflects the model's output has minimum over-segmentation and under- segmentation, which could significantly contribute to the treatment planning of hepatic diseases. The overlaid results on the input image shown in Figure 7 demonstrates the difference in the segmentation with respect to the ground truth and predicted outcome of the models. Thus, comparative analysis and segmentation results evidence that the presented model outperform than the UNet and UNet++ models.

Table 2. Quantitative result analysis of the proposed model with other models.

Methods	DC (%)	IoU (%)	VOE (%)	RAVD (%)	Precision	Recall
UNet	89.64	85.70	14.30	4.43	0.962	0.940
UNet++	95.04	92.94	7.05	2.82	0.972	0.978
M2UNet++	**97.28**	**94.70**	**5.29**	**0.62**	**0.981**	**0.992**

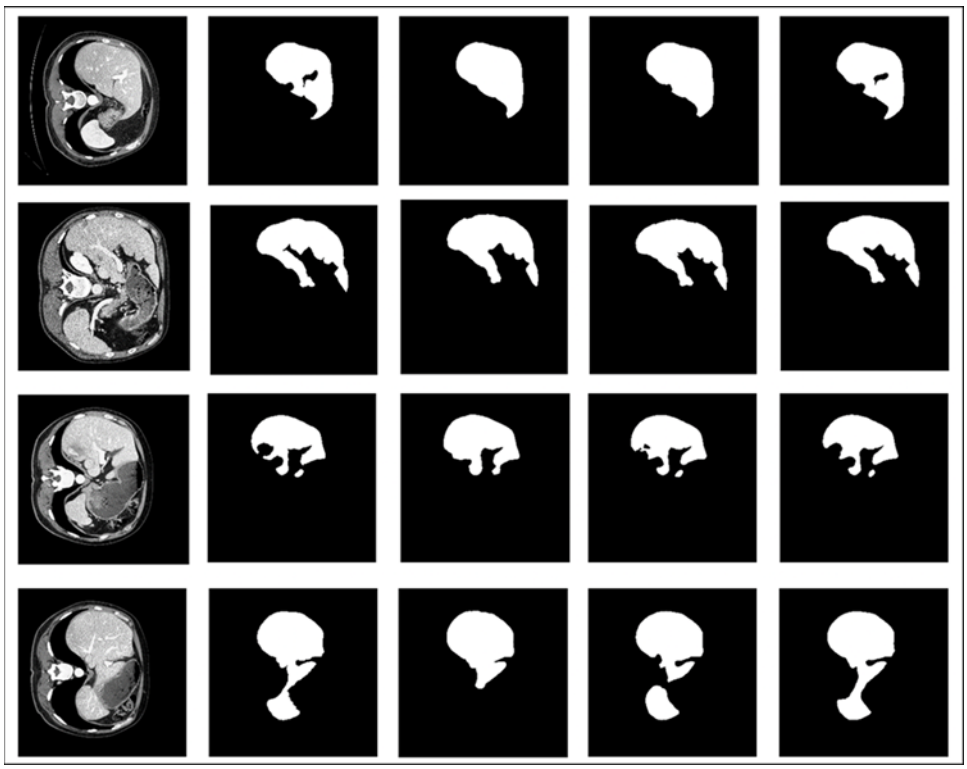
Table 3. Proposed model complexity with other models.

Methods	# Layers	# Parameters	#FLOPs
UNet	33	7,759,521	29,631,829
UNet++	86	9,041,700	34,314,010
M2UNet++	180	9,172,772	18,457,372

The model complexity presented in Table 3 shows the proposed model parameters increased by a small amount because of the channel-wise feature recalibration and the number of layers increases that elevate the model learning ability. However, the number of floating-point operations (FLOPs) reduced significantly due to modifications in the network layers. In the proposed network, conv2D operations are replaced with conv2D, batch normalization, and relu layers in the architecture. As a result, the proposed model's network parameters increased than the UNet++, but the FLOPs are reduced and segmentation performance improved significantly.

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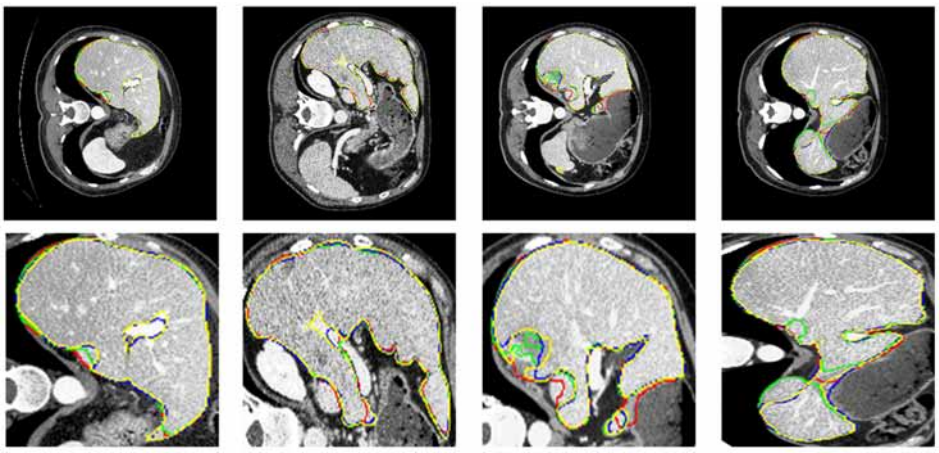
Figure 6. Sample segmentation results on 3DIRCADb test dataset: 1st column preprocessed input CT images, 2nd column respective GT, 3rd column UNet segmented results, 4th column UNet++ segmented results, and 5th column M2UNet++ segmented results.



The proposed network has the capability to segment the complex liver parenchyma accurately. In this network, the authors explored the potential of multi-scale features for preserving the high-level semantic features by modifying the skip pathways of the UNet architecture. In UNet architecture, spatial information loss occurs at each stage that hampers the network segmentation accuracy. This chapter utilized the UNet++ architecture to extract multi-scale features to recover the region of interest's semantic information and exploited the SENet to further enhance the high-level features in the skip pathways to better represent the channel-wise features. The channel-wise feature responses recalibrated to focus more on the prominent features in the image, resulting in further segmentation outcome improvement. The model is trained from scratch using supervised learning, which is dependent on the standard and volume of the dataset. The performance can be further enhanced through fine-tuning the hyperparameters, altering the data volume, and training strategies. In this chapter, the authors proved the efficacy of the UNet++ model with SENet for automatic liver segmentation.

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Figure 7. Overlaid segmentation results on the input images: GT-Yellow color, UNet-Red color, Unet++ - Green color, and M2UNet++ - Blue color.



FUTURE RESEARCH DIRECTIONS

In the future, it is possible to use this model for organ segmentation from different medical imaging modalities like Ultrasound, CT, MRI. Furthermore, the model can be utilized for the 2D or 3D medical volume segmentation in other applications like multiple organ segmentation, Brain disease segmentation, Kidney segmentation, lung segmentation but 3D models needs significantly high computational cost than 2D models.

CONCLUSION

This chapter explored the capability of the multi-scale features and channel-wise adaptive feature recalibration ability of SENet to enrich the description of high-resolution information in UNet++ architecture. The channel-wise adaptive feature recalibration focuses more on the region of interest in the input features. It emphasizes the high-level semantic information that boosts the network's learning potential, and therefore the segmentation performance is uplifted. The result analysis demonstrates that the proposed model's liver segmentation performance is superior to the UNet and UNet++ models. Thus, the M2UNet++ has the ability to segment the complicated liver parenchyma, which plays a decisive role in the treatment planning of hepatic complications. Furthermore, the M2UNet++ model could be extended to develop the medical image organs segmentation applications using different image modalities like Ultrasound, CT, MRI.

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Chapter 16
Machine Learning–Aided Automatic Detection of Breast Cancer: A Survey

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ABSTRACT

The expeditious progress of machine learning, especially the deep learning techniques, keep propelling the medical imaging community's heed in applying these techniques in improving the accuracy of cancer screening. Among various types of cancers, breast cancer is the most detrimental disease affecting women today. The prognosis of such types of disease becomes a very challenging task for radiologists due the huge number of cases together with careful and thorough examination it demands. The constraints of present CAD open up a need for new and accurate detection procedures. Deep learning approaches have gained a tremendous recognition in the areas of object detection, segmentation, image recognition, and computer vision. Precise and premature detection and classification of lesions is very critical for increasing the survival rates of patients. Recent CNN models are designed to enhance radiologists' understandings to identify even the least possible lesions at the very early stage.

INTRODUCTION

Deep Learning approach has gained tremendous recognition in the area of computer vision particularly in object detection, image segmentation and recognition (Mugahed A. Al-antari T.-S. K., 2020). Precise and premature detection and classification of lesions is highly critical for increasing the survival rates of

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persons affected. According to the statistics published by Indian Council of Medical Research (ICMR), India is likely to have over 17.3 lakh new cases of cancer causing over 8.8 lakh deaths by 2020 with cancers of breast, lung and cervix topping the list. Breast Cancer with an estimate of 8.8 lakh new cases in 2020 is likely to outnumber any other type of cancer in India. The prognosis of such types of disease is a challenging task for radiologists due to the huge number of cases together with careful and thorough examination it demands. Mammography is the most extensively used procedure for breast cancer screening and has led to remarkable reduction of death rate through prior detection. However, the complexity of mammograms, histopathological slides, MRIs and other type of scans together with massive volume of inspections per radiologist can result in false diagnosis. Computer-aided detection (CAD), employing image processing and pattern recognition techniques should provide a second opinion assisting radiologists for cancer diagnosis. Recent studies confirm CAD models cannot further significantly improve the diagnostic accuracy of mammograms in particular (Lehman CD, 2015). The main hindrance in utilizing CAD for lesion detection is high false positive rates (FPR). Moreover, there exists a trade-off between sensitivity and specificity when primitive CAD models are used. The consequence is increased patient anxiety, auxiliary radiation exposures, needless biopsies and unnecessary high health care costs. The constraints of present-day CAD necessitate new and accurate detection procedures, because millions of people undergo various types of scans each year and even a modest decrease in the FPR is an immense gain.

With the phenomenal achievement in machine learning especially deep learning, with respect to visual object recognition and detection, there is an ample scope in establishing deep learning tools to aid radiologists and enhance the accuracy of screening mammograms or histopathological slides. Contemporary research has demonstrated that deep learning assisted CAD models perform very well and also improve the radiologist`s decision making (Lee JG, 2017). In comparison to autonomous CAD systems, Convolutional Neural Networks (CNNs) attain higher accuracy results and provide quantitative analysis of suspicious lesions (Kooi T, 2016). Wang *et al.* (Wang J, 2017) have reported that Deep Learning approaches drop human error rate for cancer diagnosis by 85%.

Detection of subclinical tumour on screening mammograms is a challenging task in the classification of lesions because these lesions are immensely variable in terms of location, shape, size and texture. For example, a mammogram image is generally 4000 x 3000 px, at the same time a probable region of interest (ROI) may be as small as 100 x 100 px. This gives a good reason for many researches to focus on classification of annotated lesions. Despite the fact that classification of ROIs is a preliminary step, an automated model must process the entire input image to supplement the known information and enhance clinical interpretations. If ROIs were extensively available in medical databases, then traditional detection and classification approaches could be easily tested. However, the methods that need ROI annotations cannot be transferred to sizable mammographic databases that are scarce of ROI annotations. Proper identification of probable lesions is very essential in obtaining a high true positive rate (TPR), enhancing the diagnosis of tumours. The traditional techniques rely on less specific and hand-crafted features that lack the precision in the task of automatic detection of probable lesions. The present-day convolutional neural network (CNN) models are designed to enhance radiologist`s understanding of the identification of even the least possible lesions at a very early stage. In this article we review the latest contributions to deep learning domain in detecting and classifying lesions using various medical images.

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LITERATURE REVIEW

In order to alleviate the limitations of conventional CAD methods many researchers used a dual-stage approach, by deriving handcrafted features from the images and then using these features to train an autonomous classifier. Spanhol *et al.* (F. A. Spanhol, 2016) investigated the power of state-of-the-art handcrafted feature descriptors like Gray Level Co-Occurrence Matrices (GLCM) (Yassir Benhammou B. A., 29 January 2020), Local Phase Quantization (LPQ) (Yassir Benhammou B. A., 29 January 2020), Completed Local and Binary Pattern (CLBP) (Yassir Benhammou B. A., 29 January 2020) in association with different classifiers like 1-Nearest Neighbour (1-NN) (Yassir Benhammou B. A., 29 January 2020), Quadratic Linear Analysis (QDA) (Yassir Benhammou B. A., 29 January 2020), Random Forests and Support Vector Machines (SVM) (Yassir Benhammou B. A., 29 January 2020). Chan *et al.* (A. Chan, 2016) evaluated the performance of fractal dimension for feature description while using SVM for training and classification. The results determined that fractal dimension as unique descriptor is a better technique to classify low resolution images having less intra-similarities, but the performance gets worsened while high resolution images are classified. The outcome of using different conventional handcrafted features is considered nearly acceptable as preliminary results, though very unstable (Yassir Benhammou B. A., 29 January 2020). The main limitation of using hand-crafted features is that the quality of model relies on the extracted features, whilst obtaining rich features is extremely complex. One of the fundamental adversities is to choose an optimal descriptor among the various descriptors available and even if different descriptors are combined to improve their discriminative power for extracting best features, the results still remain weak and unstable.

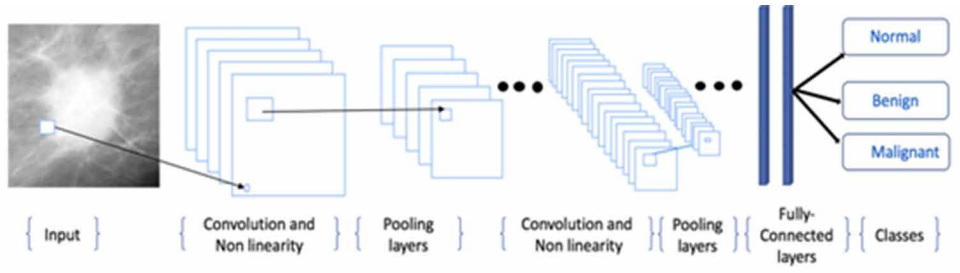
Recent practices allow deep neural networks to be used for both feature extraction as well as classification tasks and using their abilities to directly extract the most significant global features. Deep Learning is not a new concept as it dates back to 1940s for medical images (Zhu, 2019). Shallow CNNs were adopted to examine the lesions in 1995 (Chan HP, 1995) (Wei D, 1995). Deep Learning is a subset of a machine learning that requires huge amount of labelled data for training. The state-of-the-art CNN architectures like GoogleNet (Szegedy, 2015), ResNet (He K, 2016), VGG-Net (Simonyan K, 2014) and Alex-Net (Krizhevsky A, 2012) have extensively been used in medical imaging for lesion detections and classification. The popularity of CNNs can be attributed to their immense computing abilities, low-cost hardware availability and the emergence of big data (Krizhevsky A, 2012). Deep learning models require huge training data so as to be most useful. It is imperative to use both annotated datasets and large datasets along with the status of each image labelled in order to improve the accuracy of classification algorithms.

The architecture of CNNs is almost similar to that of an artificial neural network (ANN). Their layered arrangement (fig. 1) consists of a convolutional layer, a layer of non-linearity (i.e., sigmoid, ReLU, tanh etc) followed by a pooling layer (Max-pooling) and finally a loss function as fully connected (FC) layer. Convolution starts with convolving the input pixels of an image with a filter or a kernel by taking the dot product of image pixel values and kernel. If input to a convolutional layer is an image described as X_1 x Y_1 X Z_1 where X1 is width, Y1 is height and Z1 represents the number of channels (For an RGB image Z1 is 3) (Zhu, 2019). The convolutional layer consists of W filters of size M x M x Z1 where M is usually less than the dimension of input image and Z1 is same number of channels as in the input. So, we can define convolution as dot product of each of W filters with the input image so as to produce K feature maps of size X2 x Y2 x Z2. Each feature map illustrates the extracted features at various locations of an input image. Next each feature map is processed using a non-linear transformation known as activation function. The main purpose of using activation function is to prevent the neural network from

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collapsing in a perceptron. These activation functions do not alter the size of feature maps. After this, a subsampling operation known as Pooling is performed. Subsampling can be either max/min-pooling or average-pooling that is applied across the width and height of a feature map. The pooling is responsible to decrease the dimensionality of data. Finally, the output is fed to many fully connected layers which perform the desired classification task. On the other hand, CNNs require huge volume of data for training consequently training time also hits a very high value compared to both conventional supervised and unsupervised methods.

Figure 1. CNN Architecture



Recently researchers have extensively used architectures like GoogLeNet (Szegedy C., 2015), VGG-Net (Simonyan K, 2014) and variants of Resnet to classify medical images. All these architectures are pretrained on a very large ImageNet dataset that consists of 1.2 million images in training set, 50 thousand images in validation set and 100 thousand images in the test set. Training a network from scratch is usually not feasible because a dataset as large as ImageNet in is not available medical imaging.

A large deep neural network – Alex-Net (Krizhevsky A, 2012) with 5 Conv layers together with some pooling operations and 3 FC layers won the ImageNet challenge in 2012. This neural network used 60 M parameters to process a single 227x227 image. To speed up the training process it used non-saturating neurons and 'dropout' strategy to reduce overfitting. Zeiler *et al.* (Zeiler MD, 2014) introduced a visualization technique that provide an understanding about the functioning of intermediate feature layers and classifier operation. The authors introduced some minor modifications on Alex-Net and renamed the network as ZF-Net which performed and generalised well on many other datasets. A significant improvement in classification accuracy of a model is possible if depth of neural network is increased. Simonyan *et al.* (Simonyan K, 2014) asserted this statement and VGG-Net with increased depth provided better classification results on ImageNet and other datasets. GoogLeNet (Szegedy C, Going deeper with convolutions., 2015), a 22-layer deep network achieved the state-of-the-art classification and detection results on ImageNet. These results were attributed to the highly crafted design that increased the depth as well as the width of the network. A Residual network more often referred by ResNet (He K, 2016) exploited residual connections to further increase the depth of the network. ResNet is implemented with different depths. ResNet34 has 34 layers while ResNet50 is 50 layers deep. In 2015 residual network with a depth of 152 layers won the ImageNet challenge.

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Data Preparation in Medical Imaging

Many publicly available datasets lack clinical feature richness even today. Moreover, a number of aberrations exist in all medical datasets due to nature of disease and constraints in data acquisition techniques. This makes data pre-processing very essential for better training of CNNs (Yassir Benhammou B. A., 29 January 2020). The main pre-processing techniques used for medical imaging include noise removal, image segmentation and contrast enhancement. In conjugation to pre-processors, contrast limited adaptive histogram equalization (CLAHE), median filter and its variations are mostly used for reduction of noise and image enhancement. [(Teare P F. M., 2017), (Kaur P, 2016), (Bria A, 2017), (Abdelhafiz D, The Effect of Pre-Processing on Breast Cancer Detection Using Convolutional Neural Networks., 2018), (Abdelhafiz D, Survey on deep convolutional neural networks in mammography., 2017)].

In order to mitigate the issue of less training data availability, a good number of studies have used segmented ROIs (regions of interest). These ROIs are obtained by segmentation of images, further cropped and rescaled having lesion located at the centre of an image. The subsampled patches don't provide good classification results. A less precise procedure of image cropping and rescaling will result in critical information loss. To improve the patch-based classifiers either a high-resolution image may be down-sampled to 224x224 or use these patches to train a CNN that can be used as a feature extractor. In the former case, identifying tiny lesion or mass is highly rare, while the latter may serve better if a high-resolution image is split into a group of patches with negligible overlap. Finally, classification should involve patches and craniocaudal and mediolateral oblique views (Lotter W, 2017).

Nahid et al. (A.-A. Nahid, 2018) explored the obscure similarities in texture of histopathological images and used clustering for pre-processing. This approach extracted the statistical and geometric clusters from images. The clustering highlights the various nuclei masses and provide a better segmented approach for detection of lesions. Later Karthiga et al. (R. Karthiga, 2018) adopted K-means clustering on histopathological data to highlight nuclei portions followed by Discrete Wavelet Transform (DWT) to extract rich features from these clustered images. Finally, Support vector machine classifier is used for training and classification.

Data Augmentation is an artificial way of generating new data. This is achieved by applying various transformations like flipping, rotation and random scaling. Data augmentation increases the model`s ability to achieve better generalisation and avoid overfitting. Since tumours are of different and various orientations. This technique does not change the fundamental pathology of lesions therefore data augmentation becomes especially useful in medical imaging. The CNNs provide a better performance with high area under the ROC curve (AUC) when more layers are added in the network architecture. [(Teare P F. M., 2017), (Jiang F, 2017), (Chougrad H, 2017), (Szegedy C, Going deeper with convolutions., 2015)]. Nevertheless, deeper networks are able to extract more features but with more layers in the architecture, the network overfits and results in high FPR. Training deep neural networks is a challenging issue. There is a trade-off between accuracy and deep networks. Such trade-off needs to be carefully handled with trial-and-error method and nature of dataset.

Transfer Learning

Convolutional neural networks (CNNs) are highly data hungry as they require enormous data for training. Very few studies train a CNN from scratch where weights are assigned random values. Most of the research in computer vision using deep neural networks use transfer learning. Transfer Learning allows

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off-the-shelf features from powerful pre-existing deep neural architectures to be used for solving a related cross-domain problem. In transfer learning pre-existing architectures can be utilized in any of the arrangements: baseline model, feature extractor or fine-tuning the pre-trained model. In baseline model approach, only the architecture of the existing network is used while the whole network is trained on the desired dataset right from scratch. Fine-tuning the pre-trained network transfers the weights of pre-trained network to the chosen network. This can be accomplished in two ways: a) Layer specific tuning is a worthy approach that determines a subset of layers to be kept frozen whereas fine tuning the rest layers for training purposes. b) Partial training of network keeps the weights of initial layers as it is, while allowing the terminal layers to undergo training on the specific dataset. In Feature Extractor arrangement of transfer learning the convolutional base of pre-trained network is used without weight alteration for extracting the most discriminating features. The output of this convolutional base is given to a classifier for performing classification task. The required arrangement of transfer learning is application specific. Layer specific tuning offers a comprehensive and practical procedure to achieve better performance.

A good number of the studies deploying Transfer Learning technique have used ImageNet for pre-training the network (Huynh BQ, 2016), (Lévy D, 2016), (Suzuki S, 2016), (Jiang F, 2017), (Samala RK, 2017), (Mohamed AA, 2017), (Wei X, 2017), (Xi P, 2018), (Zhang X, 2017)]. Alex-Net (Gallego-Posada J), (Lévy D, 2016), (Suzuki S, 2016), (Jiang F, 2017), ResNet (Xi P, 2018), (L, 2017) and GoogLeNet (Domingues I, 2012), (Jiang F, 2017), (Xi P, 2018) are the most commonly used pre-trained CNN architectures for medical imaging. All these pre-trained networks are trained on ImageNet that is designed to perform 1K classifications. In order to make these pre-trained networks the last three layers are replaced by new FC, Soft-max, classification layers respectively. Until massive medical image datasets are made available, the union of Transfer learning and artificial augmentation of data will prove to be the most effective model of training deep neural networks.

Evaluation Metrics

In order to perform the quantitative evaluation, various weighted metrics are used for lesion detection and classification. A number of studies have used cross-validation techniques to evaluate discriminative models. It is a statistical approach that randomly partitions the original dataset into a training set that is used to train the model, and a test set for evaluation. This cross validation can be used in three variants. Hold-out variant of cross validation randomly partitions the original dataset into training set (80%) and test set (20%). All evaluation metrics are performed on test set. Another variant known as three-way data splits again randomly partitions the dataset into three partitions – training set, validation set and test sets. The model is trained on training set and is initially evaluated on validation set. A repetition of training and validation is performed a number of times till a model with best possible weights is found. Finally, this well-trained model is evaluated on test set. K-folds type of cross validation splits the data into k subsets. The validation process considers each of the k subset exactly once and the model validates across each subset. Finally, all the k values are averaged to provide a single estimated value. Among the three validation variants most of researchers have used k-fold cross validation (k = 3-5) for medical imaging.

In order to perform a fair evaluation of different predictive models, various studies have proposed many metrics for classification task. Image level accuracy (ILA) defines classification accuracy at different image levels and doesn't take into account any patient specific information. It is defined as the ratio of correctly classified test sample images (S_{co}) to total number of test sample images (S_{to}).

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$$ILA = \frac{S_{co}}{S_{to}} \tag{1}$$

The second metric measures the performance of predictive model at patient level. This patient level accuracy is the ratio of correctly classified test sample images (to the total number of test sample images) for a particular patient .

$$PLA = S_{P_{co}} / S_{P_{to}} \tag{2}$$

These two metrics are used when dataset distribution is balanced. While training the model on an imbalanced dataset, many studies have evaluated their predictive models using metrics like F1-score or Area Under Curve (AUC) (M. Sokolova, 2006). These metrices are directly related to model`s sensitivity towards positive cases. F1-score is defined as the harmonic mean between Recall and Precision.

$$F1 = \frac{2 \times Recall \times Precision}{Recall + Precsion}$$

Where:

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

And $$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

AUC measures the trade-off between recall and false positive rate. It allows a classifier to be evaluated over all possible thresholds. This makes AUC the broader metric among all metrics discussed so far.

Automatic Image Retrieval

For segmentation of mammograms, it is imperative to find precise regions of interest. The abnormal tissue or masses can have different variants which include micro-calcifications, circumscribed masses, speculated and many more. There is very less morphological distinction between these masses. So, it becomes very difficult to accurately segment the area of interest, making the task of retrieval less accurate. This is the main reason for an automatic content-based image retrieval to discover feature rich regions of interest. A boundary-based segmentation technique was proposed by Wei et al (Wei, 2012). This content-based mammogram retrieval identified seed points which are the brightest pixels in any region of interest. Different thresholds were tested on a sample of 100 images and then final threshold was set. Qayyum et al. (A, 2017) proposed deep neural network aided framework called Content based Medical Image Retrieval (CBMIR). The framework trains a CNN to perform classification task using

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diverse medical image dataset comprising of images of various human body organs. They achieved a classification accuracy of 99.7% for 24 classes.

CNN based Lesion Detection and Classification in Medical Images

Lesion detection in medical images using deep CNNs (Histopathological images or Mammograms) is a common practice with researchers. It is important to highlight the exact location of affected tissue. Li shen et al (Shen, 2019) used CNN for classification of screening mammograms. The authors performed independent tests on two separate datasets – DDSM and Inbreast. The fine-tuned model achieved a per image AUC of 0.88 and four model averaging further enhanced the AUC to 0.91 on DDSM dataset. For INbreast dataset an AUC of 0.95 and 0.98 was achieved for single model and four-model averaged respectively.

Ben et al. (Ben-Ari R, 2017) proposed a lesion detection method by studying architectural distortions using a pre-trained region-based network namely R-CNN. Ertosun et al. (Ertosun MG, 2015) designed an end-to-end approach for localization of masses in mammograms. Hwang et al. (Hwang S, 2016) adopted an independent transfer learning approach for lesion localization that does not require any pre-requisite information about location or any pre-trained networks. Patch based CNNs were studied (Sun W, 2016) (Dhungel N, 2015) (Choukroun Y, 2017) for detection of any masses or calcifications. A deep neural network extracts distinctive features from image patches which are used for localization of tumours. An end-to-end training method is employed for segmentation of masses augmented with proper pre-processing and image-enhancement help to improve ROI characteristics of medical images (Zhu W, 2016).

In comparison to lesion detection, classification of medical images either as multi-classification or as binary classification is very difficult. Most of the studies restricted classification of lesions into benign or malignant (two-class or binary classification). A few more studies used deep CNNs to classify images into three classes benign, malignant and normal. Han et al. (Z. Han, 2017) designed a two-stage procedure in which a multi-class classification phase follows a binary class classification phase. This two-stage framework is used on histopathological dataset. The dataset includes various sub-categories of the two main classes i.e., benign and malignant. The model initially derived the sub-class of an image while the main class was deduced intuitively. Authors observed high degree of similarity among the instances of the same sub-class as compared to those having different sub-classes. Moreover, the importance of data augmentation and transfer learning was also highlighted for obtaining better multi-category classification results.

A recent study (Z. Gandomkar, 2018) initially used pre-trained ResNet-152 for two-class classification. Later the model was fine-tuned to perform multi-class classification. The first phase identified the main class, while subsequent phase provided the sub-class of the instance. While evaluating the model it was considered valid only if outputs were classified correctly at both stages. A merger of localization and classification, what is more commonly referred as multi-class localization is an end-to-end approach initially classifies the images and later on performs localization procedure on the same images. A deep neural network using YOLO [(Platania R, 2017) (Al-Masni M, 2017)] localizes the mass calcifications and classifies them as benign or malignant. This approach achieved classification accuracy of 96.3% and detection accuracy of 85.5% (Al-Masni M, 2017).

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Table 1. Classification Techniques and findings

Technique	Pre-processing	Feature Extractor	Transfer Learning	Patch/WSI	Dataset	Classifier	Metrics
Ertosun et. al., 2015	Data Augmentation with cropping, translation, rotation, flipping and scaling.	CaffeNet	ImageNet	P(256x256px)	DDSM	AlexNet, VGG16, GoogLeNet	ILA
Dhungel et. al., 2015	None	CNN and DBN	None	WSI	DDSM and INbreast	CNN and DBN	Dice Index
Bayramoglu et. al., 2016	Data Augmentation with cropping, translation, rotation and flipping.	Deep CNN	ImageNet	WSI	BreakHis	Deep CNN	ILA, PLA
Chan et. al. (2016)	Binarization	CaffeNet	None	WSI	BreakHis	LR	F1
Gallego et. al. (2016)	Data Augmentation with cropping and rotation, resize (224x224, 227x227)	AlexNet and VGG16	ImageNet	Random patches (224x224, 227x227)	MIAS	SVM	ILA
Spanhol et. al., 2016	Resize(350x230), Subtracting mean images.	ALexNet	ImageNet	Random patches (32x32) and Sliding window patches (64 x 64)	BreakHis	AlexNet	ILA, PLA
Akbar et. al., 2017	None	AlexNet	None	P(228x228)	BreakHis	AlexNet	ILA
Wei et. al., 2017	Data Augmentation with rotation, scaling and mirroring.	GoogleNet	ImageNet	WSI	BreakHis	GoogleNet	ILA, PLA
Han et. al., 2017	Data Augmentation with flipping and rotation, intensity variation, flipping and translation.	CSDCNN	None	WSI	BreakHis	CSDCNN	ILA, PLA
Ben-Ari et. al., 2017	Data Augmentation with rotation and flipping, resize(128x128)	VGG16	ImageNet	Random patches (128x128)	DDSM	VGG16 and CaffeNet	ILA
LIM et. al., 2018	Data-Imbalance under sampling	VGG16	ImageNet	WSI	BreakHis	InceptionV3	ILA
Badejo et. al., 2018)	None	LPQ	None	WSI	NA	SVM	ILA, AUC
Nawaz et. al., 2018	Resize(224x224)	DenseNet	ImageNet	Random patches (224x224)	BreakHis	Modified DenseNet	ILA, PLA
Abdullah et. al., 2018	None	CNN, LSTM	None	WSI	BreakHis	CNN and LSTM	ILA, F1
Benhammou et. al., 2018	Subtracting mean images	InceptionV3	ImageNet	WSI	BreakHis	InceptionV3	ILA, PLA, F1

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Table 1. Continued

Technique	Pre-processing	Feature Extractor	Transfer Learning	Patch/WSI	Dataset	Classifier	Metrics
Bardou et. al., 2018	Data Augmentation using rotation and flipping.	Deep CNN	None	WSI	BreakHis	DeepCNN	ILA
Bardou et. al., 2018	Resize(227x227)	AlexNet	ImageNet	WSI	BreakHis	AlexNet	ILA
Shen et. al., 2019	Data Augmentation with horizontal and vertical flipping, zooming and intensity shift.	ResNet-50	ImageNet	WSI and P(224x224)	DDSM and INbreast	ResNet-50 and VGG-16	ILA
Jiang et. al., 2019	Data Augmentation with height and width shift, horizontal flipping.	BHCNet-3	None	Random patches (224x224)	BreakHis	BHCNet-3	ILA
Sharma et. al., 2020	Resize(224x224)	Color Histogram and Haralick textures.	ImageNet	Random patches (224x224)	BreakHis	CNNs (VGG16, VGG 19 and ResNet50)	ILA, PLA
Mugahed et. al., 2020	Data Augmentation with rotations, flipping, scaling and translations.	YOLO	None	WSI and P (128x128, 224x224, 299x299)	DDSM and INbreast	InceptionResNet-V2	ILA
Karan et. al., 2020	None	CNNs (ResNet, VGG16, VGG19 and Xception)	ImageNet	WSI	BreakHis	SVM and LR	ILA

Literature Analysis

After a critical review and evaluation of related literature, the following enlisted research challenges call for further investigations:

1. Tumour Localization

The Convolutional neural networks and their variants like R-CNN, Fast R-CNNs and YOLO methods have been mostly used in recent studies for object (lesion/tumour) localization. R-CNNs require very large data and memory for training. This makes them computationally very expensive. While YOLO based approach is fast and requires less computational power but it proves to be less accurate for object detection (Mugahed A. Al-antari S.-M. H.-S., 2020). So, more efforts are needed for better localization of tumours in medical images.

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2. Limited Medical Data

Small sized publicly available medical datasets pose a major challenge for researchers to train a CNN. Data Augmentation technique, of course, is used to provide some help but the problem has still not been solved.

3. Imbalanced Data-Set

Unequal proportions of positive and negative classes in the training data-set may bias a classification model towards more common class. The effect of imbalanced data-set on the performance of a CNN has not been studied thoroughly on medical data-sets. It is important to investigate the effect of balanced and imbalanced data-sets on the accuracy of CNNs.

4. Size Irregularities of Lesions

The varying size of lesions within the samples is another constraint for effective training of CNNs. A common practice with most of the researchers is to resize a large sample to 224x224 or 227x227. Reducing the original size will make it hard for a CNN model to detect or classify a lesion. More research has therefore become imperative to train a CNN at different lesion scales.

5. Training a Model on a Non-Annotated Data-Set

Majority of the publicly available datasets are non-annotated. These non-annotated data-sets contain images which are labelled either as cancerous or normal, which lack any additional information about the location of abnormality. Training CNNs on such datasets is still an open area of research.

6. Using Pre-Processing Techniques

A number of samples collected from patients are misdiagnosed because the lesion may be less prominent or may have a poor contrast that could reduce the sample qualitatively. In order to mitigate these problems good image processing techniques are required to be investigated for choosing such an appropriate pre-processing filter is an open issue till date.

7. Multiple Lesion Detection

Present deep neural networks are trained to detect and classify a single type of abnormality within a sample image neglecting any other type of calcification/mass if present. Deep neural networks need to be trained adequately to detect multiple abnormalities within a same slide.

CONCLUSION

Malignancy can appear in medical images (mammograms, X-rays, histopathological slides) as mass depositions, microcalcifications and architectural distortions. Generally, the morphological features

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like size and shape of such abnormalities together with their density and distribution indicate the nature of malignancy. Radiologists manually investigate the appearance of damaged tissues and estimate the potential cancer risk using specific metrices. This work presents findings of a number of studies outlining the limitations of current Computer-aided detection (CAD) techniques and impresses upon the use of deep neural networks which have shown a good promise in detecting lesions more accurately giving a glimpse of hope to radiologists for accurate diagnosis. Moreover, a detailed insight of convolutional network architectures used for a number of tasks in medical imaging is also presented.

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Chapter 17
ML-Enabled Informed Intervention for Crowdsourcing-Based Optimization of Medical Resources

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ABSTRACT

It is said that every adversity presents the opportunity to grow. The current pandemic is a lesson to all healthcare infrastructure stakeholders to look at existing setups with an open mind. This chapter's proposed solution offers technology assistance to manage patient data effectively and extends the hospital data management system's capability to predict the upcoming need for healthcare resources. Further, the authors intend to supplement the proposed solution with crowdsourcing to meet hospital demand and supply for unprecedented medical emergencies. The proposed approach would demonstrate its need in the current pandemic scenario and prepare the healthcare infrastructure with a more streamlined and cooperative approach than before.

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INTRODUCTION

Data points to predict the progression of Covid-19 have highly researched, making the work for epidemic spread research considerably easier. Though the epidemic spread models helped overcome significant roadblocks in managing Covid-19 challenges, the research slightly overlooks the most important aspect, hospital resource planning and management. The research documented the challenges faced by hospitals during the pandemic, but either from the perspective of managing other health treatments in the wake of Covid spread (Korytkowski et al., 2020; Ueda et al., 2020) or managing individual units (Kotfis et al., 2020). The researcher also mentioned challenges faced by medical professionals (Sethi et al., 2020; Spoorthy et al., 2020).

Further, the research extended to learn the hospital resource management during the Covid-19 pandemic. The spread of Covid-19 through human-to-human contact could be minimised by using protective gear such as PPE (Personal Protection Equipment) kits, gowns, masks, and protection kits for respiratory systems and eyes. Medical resources like PPE kits and other protection gear not be stored in hospitals in large quantities. Thus, taking a proactive approach to managing the supply of essential protection gears is a requirement of the hospital management during the course of stirring the Covid-19 pandemic. There were reports of limited supplies of critical protection for health workers (Grimm, 2020).

The problem of effective hospital management is not even new; in 2016, the founder of Logistics Bureau stated:

It's widely recognised that internal hospital logistics is even more complex than the external side and that medical staff spend disproportionate amounts of paid time performing logistics activities—time which would be better used to provide patient care. - Rob O'Byrne (Logistics Bureau, 2016).

In the early period of the Covid-19 epidemic spread in India, the hierarchical structure of health management was implemented, including Dedicated Covid-19 Hospitals (DCH) and Dedicated Covid-19 Health Centers (DCHC). The report published on June 2020 (Times of India, 2020) mentioned that the fatality rate due to Covid-19 in India was 2.83%, but there was continuous transmission rate growth. On the other hand, the recovery rate was slow. The statistics of June 3, 2020, stated that the bed occupancy of DCH and DCHC was already 94%, i.e., ICUs were running with a capacity of 98%, and 85% of ventilators were occupied. Now after almost 11 months these statistics have not yet improved much. As of April, 25 2021, the bed occupancy of DCH and DCHC is 80.303%. ICUs were running with a capacity of 98.30%, and 98.41% of ventilators were occupied. Upscaling the hospital resources at a given time posed a significant problem with the existing setup. Thus, the authors realised the need to comprehend and predict the stage wherein the utilisation of hospital resources reach 100% is a requirement of healthcare infrastructure.

The other challenge that emerged for hospital infrastructure management during a pandemic is meeting the need for non-Covid-19 medical emergencies such as cancer treatment, diabetic treatment, dialysis treatment, and so on (Kuhlen et al., 2020; Ralli et al., 2020; Ueda et al., 2020). The hospital infrastructure has realised the need for minimum preparedness for teleconsultation with patients, such as updating the patient's record digitally, creating a digital record of the patient's current state from his/her home. The health sector realises the need for patient data omnipresence to handle unprecedented medical situations during a pandemic.

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Though the researchers studied medical informatics in the past few years, as mentioned in (Asadzadeh et al., 2020), the medical domain's applied IT (Information Technologies) setup is neglected. The work presented gaps in existing IT technologies to contain medical emergencies such as the Covid-19 pandemic. The utilisation of IT technologies to predict epidemic and manage health services during a pandemic is of utmost importance.

Medical informatics is an amalgamation of Information Technology with different disciplines of medicines for efficient health services. The pandemic role of medical informatics is studied to comprehend the implementation and effectiveness of various medical services.

The focused study is presented in (Eslami HassanAbady & Ganjali, 2021) to address research questions like which medical informatics tools were used during the Covid-19 pandemic, what methods refer to studies related to medical informatics tools, and the quality of these studies? The study established the premises that medical informatics would navigate the upcoming health services.

Studies emphasise the employment of Artificial intelligence (AI) based tools and techniques to curb the pandemic's spread. Also, the AI-directed approach will significantly reduce the patients' response from detection of infection till the disease's cure. The AI can be used in various disciplines of medical services such as managing health care, tracing infected patients, assisting health workers. In work (Vaishya et al., 2020), authors proposed AI-based approaches, including early detection of patients, developing vaccines, and managing health professionals' workload.

Also, digitisation of hospital infrastructure is addressed by weighing strengths, weaknesses, opportunities, and challenges. In (Kapoor et al., 2020), the authors mentioned medical community would witness the change in structure in curbing pandemic. The changes will range from robotic assistance, teleconsultations, wearable devices, and interactive decision-making tools with better data visualisation.

In work (Sudat et al., 2021), the authors documented that the EHR (Electronic Health Records) system suffers from drawbacks like inefficient real-time report generation, limitation of manually inputting data points, and heterogeneity in patient data collection. The authors also recommended covering the gap between clinical and data analysis so that EHR data could be fully utilised.

The more focused study towards health-related data in digital form is addressed in (Celuppi et al., 2021). The presented work aimed to attain two objectives: first, to research digital health technologies and practices used in Brazil and the world during pandemic and second was to weigh digital health technologies' effectiveness during a pandemic. The authors presented work through a literature review with keywords 'digital health technology' and 'Covid 19' during July 2020. The work mentioned that various forms of digital health technologies have demonstrated during pandemic ranging from clinical data analysis, teleconsultation, contact tracing apps.

Thus, it is established that digital technologies are capable enough to facilitate and improve existing and upcoming health services. Therefore, to seek for new technologies could be promoted to offer quality health management.

The Covid-19 pandemic is not the first pandemic of the century. The Twenty-First century has faced medical emergencies such as SARS (Severe Acute Respiratory Syndrome, HPAI (H5N1 Highly Pathogenic Avian Influenza) virus, H1N1 influenza. The medical emergencies have motivated researchers to estimate the likelihood of health infrastructure during the pandemic. Several studies have been published to address the preparedness of health services for the upcoming pandemic. For example, the resources sharing of health services is discussed in work (Hanvoravongchai et al., 2012) in 2012. The authors pointed out the heterogeneity of resources in the Greater Mekong Subregion (GMS) of Asia. The study mentioned that the resources like health workers, ventilators, hospital beds were unevenly distributed

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across the GMS population. The work concluded the sharing and mobilisation of resources are recommended during a pandemic scenario in the GMS.

The researchers have proposed hospital resource planning approaches over the past decade, including stockpiling the ventilators (Huang et al., 2017). The authors discussed the optimisation framework to stock ventilators in central and local repositories to handle excess demand in future pandemics. The study presented the case study of Texas, US, assuming a mild, moderate and severe pandemic scenario when respiratory failures during influenza result in the need for ventilators.

The optimisation approach was confirmed with two risk scenarios. The first scenario considered an estimated number of patients with ventilator support requirement does not receive the necessary support. The second scenario was at least one patient does not receive ventilator support. The authors commented that the trade-off between risk and stockpiling cost was minimised by limiting stockpiling to the specific threshold at central and local repositories. The work discussed the opportunities and challenges associated with central and local repositories. With retrospective data, authors also commented that Texas hospitals' ventilator supply was enough to handle moderate pandemic but would fail in case of a severe pandemic. The current Covid-19 pandemic situation has proved correct with the mentioned claim.

The health resource planning during pandemic has researched over deace with various aptitude and attitude. One such perspective is exploring the simulator and the tool-based approach for hospital resource planning to simulate the resource planning and estimate the severity of disease spread. A simulator like Fluserge 2.0 (Zhang et al., 2006), developed by the CDC (Centers for Disease Control and Prevention) of the US, simulated the need for hospital resources, namely beds, ventilators and ICU beds, as pandemic progresses.

The simulators like AsiaFluCap (Stein et al., 2012) further offered comprehensive information to policymakers by combining the epidemiological model with 28 health care resources model. The purpose of AsiaFluCap, a free simulator, is to help policymakers prepare for the upcoming pandemic. The discussed simulator has features like estimating the 28 hospital resources, including PPE kit, medications, body bags during the surge of a pandemic. The scenario-based dynamic modelling with AsiaFluCap allows researchers to create a map using GIS (Geo Information System) based software.

One such tool-based study (Gul & Yucesan, 2021) proposed a hospital preparedness assessment against the Covid-19 pandemic using the TOPSIS decision-making method alongside its IVSFS extension. The proposed approach is applied to rank three Turkish hospitals serving as tertiary healthcare services. The paper has adapted and used ninety-nine subcomponents under ten components in the model initially reported by the WHO (World Health Organization) in 2020. These components are concerned with the patient surge, infection monitoring and control, human resource, case management, communication, supply chain management, laboratory services, surveillance, and essential services.

Further, the pandemic has proven difficult to be handled in an isolated way by any healthcare facility providers. Thus, it might be a good opportunity to explore the collaborative work for efficient resource handling in a crowdsourcing manner. Crowdsourcing facilitates to attempt of the solution of individual organisation cooperatively by a group of people.

In work (Schaye et al., 2020), the researchers documented findings of collaborative sharing among four hospitals. In New York City, four hospitals, the Grossman School of Medicine in private and public hospital setting, Department of Medicine, New York University, Veteran Affairs federal hospital, attempted collaboration for communication, managing surge capacity, Triage response, Staffing, and staff care clinical care. The study elaboratively covered the strengths of cooperation in the health community. The study documented that collaboration opted for two hospital system where one hospital is identified

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for Covid-19 patients, and another hospital admits non-Covid-19 patients. Also, the fund generated by one hospital is shared among the partnered hospital up to a certain extend. The resources available with one hospital in terms of meditation training, therapy was collaboratively shared among partnered hospitals. However, there is no direct formal mention of crowdsourcing the resources among hospitals. The case study of New York City strengthens the claim that it is very much possible to share resources among the hospital community with related stakeholders' involvement.

One form of partnership among hospitals is addressed in (Archbald-Pannone et al., 2020). The Post-Acute and Long-Term Care Facilities (GERI-PaL) and regional academic medical centre joined hand to run the Geriatric Engagement and Resource Integration program in Post-Acute and Long-Term Care Facilities (GERI-PaL) '. The study claimed that it was a successful attempt to collaborate with interprofessional teams.

Direct attempt in the direction of cooperative working among hospitals was discussed in (Pick et al., 2021). The Critical Access Hospitals (CAH) partnered with local public health departments. One form of partnership undertaken by the mentioned relationship was managing Covid-19 test supplies, donating PPE kits. The collaboration between local and state level hospitals alleviated the burden of managing pandemic up to a certain extends in a rural area. But no statistics were produced to confirm the success of such a partnership.

Still, the concept of Crowdsourcing seems far fetched in the medical domain, but the researchers are inching towards employing Crowdsourcing for the betterment of the medical sector. One such attempt during a recent pandemic is documented in (Brown et al., 2020). In the mentioned work concept of Crowdsourcing is involved in collecting data on uncontrolled conditions. Authors created web and mobile applications through which users/ participants could record their respiratory sound.

The objective of the work was to prove the hypothesis that among many other diagnostic markers to identify the Covid-19 symptoms, human respiratory sound can be confirmed as one such marker. The work developed a framework to collect sound through the means of Crowdsourcing. The framework was succeeded in collecting 7000 sounds from distinct users, strengthening the process to establish the researchers' proposed hypothesis.

Thus, the literature points towards the fact that the digitised and cooperative model of managing health resources is needed in the healthcare industry.

The present chapter discusses the solution proposed to machine learning-based informed interventions to allow hospitals to manage resources more efficiently and to move to a paperless approach for more excellent reliability and omnipresence of data. Further, the proposed solution aims to assist the hospital with predictions for future inventory requirements. Also, the option of crowdsourcing the hospital resources among hospitals in the nearby vicinity to meet challenges of resource management and planning is discussed in the proposal.

The objectives of the proposed solution are as follows:

- Patient/Report record management system
- Inference derivation and correlation-based upon patient data
- Inventory predictions and Resource optimisation with Crowdsourcing

This chapter proposes a solution to visualise patient data with features like adding new patients, managing patient reports, and optimising hospital resources' inventory. One of the proposed solution modules, a Patient Trend Spotter, presents interactive visualisation of every patient in the hospital and

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displays recovery progression in a patient. The statistical measures are inbuilt to derive inferences and correlation from patient data to confirm the pattern of disease progression or patient recovery. An interactive dashboard will allow the hospitals to view the utilisation of hospital resources, trends of patient recovery, and related statistics in one glance. The hospital can track inventory usage. Based on patient progression, predictions for future inventory are made, and the hospital personnel can take the required steps to meet the demand. The module of Inventory management will keep track of the hospital inventory (medicine and equipment) and corroborate with other hospitals in cases of emergency requirements.

The novel contributions of the proposed work are:

- Digitising the patient data in line with hospital data collection and protection policy
- Interconnectivity between inventory module and patient module to keep track of the status of inventory and to predict the future need of inventory
- Facilitating the crowdsourcing platform among hospitals to demand and share resources

The following chapter arranged as follows: the background section covers literature work documented in the direction of identifying challenges and solutions concerning proposed work. The next section of the background is a discussion on the proposed approach. The chapter concludes with the formal conclusion and future scope.

BACKGROUND

The recent pandemic of Covid-19 exposed the limitation of existing healthcare infrastructure to handle challenges associated with unforeseen medical calamity. The global Covid-19 pandemic has directed an unprecedented load on hospitals worldwide. The earlier spread of the pandemic caused a massive influx of patients in hospitals. To handle the influx of patient, hospitals were forced to dedicate considerable resources and staff. The time taken away from patient care is not ideal for any healthcare system, and neither is the unavailability of medical reports or healthcare equipment.

The proposed chapter offers patient data management extended with analysing capabilities, leading to hospital resource usage optimisation. Further, the proposed solution utilises Crowdsourcing's concept to handle the demand and supply of hospital resources in medical emergencies that are not limited to restricted to handling pandemic.

The pandemic has underlined the need for digitisation of the hospital record management system. Electronic Health Record (EHR) management is discussed in the literature (Mathai et al., 2017). The researchers concluded that though hospital management needs the EHR, particular challenges like a data breach, cyber attacks, and privacy-related concerns must be addressed.

In work (Singh et al., 2020), the authors mentioned 'Health information technology (HIT) ' in which advanced information technologies like cloud computing, Internet of Things play important roles. With the availability of electronic health records and various services like the Patient management portal, tracking inventory can be facilitated to provide adequate health services. Typically, in situations like a pandemic, the HIT could enhance feasibility and practicalities for interhospital and tele-healthcare communication.

In work (Faraj et al., 2021), the authors mentioned that the Covid-19 pandemic opened the issue to health care stakeholders about digitising records. The authors pointed out that uneven patterns observed in providing digitisation infrastructure, especially when the rural areas were concerned. The work argued

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that the population with inadequate health services infrastructure to access and generate digital records tends to suffer more during the pandemic. The questions put forward to policymakers were whether to address adequate digital infrastructure in hospitals as right than a privilege and effectively manage supply chains. Also, the policymakers must resort to managing data security and privacy, identifying and bridging the gap between data conversation from analog to digital form.

Most hospitals supplement themselves with patients' record management, but not much is discussed about how the existing platforms are extended to manage challenges stand out due to the Covid-19 outbreak. In work (Anaikatti et al., 2021), the authors elaborated on how current hospital information management platforms strengthen with ' identify-isolate-inform strategy'. In Singapore at Changi General Hospital, the existing Electronic Medical Record (EMR) was updated to meet patient management and monitoring during the pandemic. The case documented by the Singapore hospital also highlights the need to update existing patient data management platforms to accommodate points like the patient's travel history. Thus it is essential for hospital management systems to be flexible in design to incorporate as much data as possible to handle unprecedented medical emergencies.

The researchers attempted to establish the necessity of healthcare infrastructure in response to epidemic spread (Saunders-Hastings et al., 2017; Stein et al., 2012).

In this particular study (Boccia et al., 2020), the authors offered a perspective on Italy's health setup, including the average of its population and comorbid conditions among the population. Italy has a population with higher Age compared to other European countries. The study mentioned that hospital management should consider age structure and average health condition of the population to attempt preparedness of health infrastructure with capable Intestine Care Units. The research presents statistics on ICU beds in Italy's hospital setup. The effective management of available resources lacked in Italy as initially, patients with mild symptoms were admitted to the hospital. As Covid-19 spread outbreak, the patients with severe symptoms could not admit to the hospital. Also, the infection spread increased in hospitals, which resulted in a higher number of medical personnel being infected. The study pointed out that some regions might be most likely to be not worse with infection than the others. Also, the prediction about whichever hospital could take maximum load is unpredictable. Therefore, what is required is a prepared hospital with extra resources like ventilators. The study concluded on the note that the health management system could better allocate the resources.

While addressing challenges associated with Covid-19 pandemic, in the earlier days of the pandemic, the term "flattening the curve" was widely discussed; what it implies is to keep safe so that the present hospital resources do not get exhausted causing the healthcare to crumble under pressure.

In Maharashtra, India, the Government Hospitals used a staggered approach wherein a hierarchical structure of treatment centres was created. At the lowest level were CCC (Covid Care Centers), those who took care with mild or very mild or as suspect cases, and the higher in order were DCH and DCHC. The said arrangement was made to have appropriate utilisation of resources of health infrastructure.

During the initial spread of Covid-19, there was a massive influx of patients in hospitals, requiring an infrastructure to handle and analyse all the data. The capable infrastructure to handle the sudden increase of admitted patients was widely amiss and caused hospitals to dedicate considerable resources and staff to collect and organise patient data.

Due to the current pandemic, health infrastructure professionals are forced to look at the health infrastructure with fresh eyes. The unavailability of hospital resources to patients is one reason to decrease health professionals and patients' morale. The researchers have documented findings of limited resources

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during a pandemic (Garg & Wray, 2020; Peiffer-Smadja et al., 2020; Verma et al., 2020; Weissman et al., 2020).

The Machine learning (ML) based approaches to managing essential hospital services, such as predicting emergency wards' capacity, were discussed in the literature before pandemic as well. In work (Graham et al., 2018), the authors employed data mining-based approaches, including linear regression, decision trees, and Gradient boosted machines to predict the emergency ward's capacity to admit incoming patients. The data considered for prediction consists of the hospital's location, admitted patients records including Age, date of admission, statistics related to the number of patients admitted in last month, number of patients admitted in the previous year during the same period. The study's objective was to use data for better resource planning to divert excessive influx of patients to other hospitals. As per observations presented in the work, more than one ML approach would be helpful for better and accurate results.

The pandemic has forced all health industry stakeholders to address practical solutions to handle emergencies like the current pandemic from the perspective of resource management and utilisation. The authors (Haleem & Javaid, 2020) presented a review on the Medical 4.0 revolution. The Internet of Medical Things equipped with an intelligent support system could be the future for the health industry.

The study (Qian et al., 2021) presented in July 2020 attempts to forecast the need for hospital resources nationwide. The 'COVID-19 Capacity Planning and Analysis System (CPAS)' is a machine learning-based system deployed nationwide in the UK with the NHS digital to forecast ICU resources' demand during the pandemic. The CPAS handled capacity planning for ICUs with a machine learning-based approach. Keeping in mind, the setup created during a pandemic needs to function and effective even after a pandemic. The capacity planning refereeing to ICU demands in CPAS is done on four levels – Patient, hospital, region, and nation-wise. The model intended to give a bird-eye view of ICU demands in the nation.

In contrast, interhospital demands could model at the regional level under situations where ICU demand is higher in one hospital than in another. At the hospital level, CPAS estimates the status of demand and supply of ICU resources. At the patient level, individual Patient profiles could evaluate to predict the possibility of a patient's requirement to shift to the ICU.

In another study in Denmark (Sloth Lorenzen et al., 2021), the authors tested the ML-based approach's usefulness for better logistic management. The ML models such as Random Forest trained to predict whether patients could develop severe symptoms, resulting in ventilators' need and shift to ICU. The prediction used a window of five days and ten days during which patient recovery monitor. The work refers to micro projection where the individual patient is analysed for risk prediction and macro prediction where the hospital predicts resources. The micro and macro prediction could be possible with the availability of patient health data digitally.

Also, in parallel studies, the researchers estimate ICU bed capacity. In work (Cao et al., 2020), researchers confirmed that there is no binary answer to ICU bed capacity in hospital infrastructure. If ICU beds are fewer, it may hamper patient care, and if ICU beds are greater in number, it may increase hospital budget. Thus, the ICU capacity is left to the discretion of hospital management. But during Covid-19, the researchers (Michard et al., 2020) examined whether it is beneficial to increase ICU beds or better incorporate a smart management facility in the hospital.

In work (Lacasa et al., 2020), the authors presented a study referring to data from UK and Spain. The objective of the work was to estimate additional ventilators in the UK. The authors of the paper proposed a flexible algorithm to transfer the ICU patient or the patient requiring ventilators. The work attempted the

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nearest neighbour approach for rerouting the patients. The load sharing capacity was estimated with the random forest algorithm. The authors mentioned that with the initial steps of the proposed algorithm, 1000 ICUs could be accessible in the UK. Further, the study concluded that assuming heterogeneous demands and health setup like Spanish where hospital facilities have not collaborated; still, the algorithm could offer 600 ICUs considering collaboration at local facilities and 1300 ICUs over countrywide facilities.

There are no common platforms that have the implementation of allowing for hospitals to request resources from other hospitals. The attempts, like ValueCoders' Individual practitioners' application (Valuecoders, n.d.), PixelCrayons Health Tracking App (pixelcrayonsTM, n.d.), and Chetu's Electronic health record (Chetu,), do exist. Still, none cover the aspect of collaboration with other hospitals or resource utility prediction. The comparison of the same I shown in the bellow Table 1.

Table 1. Comparison of COMRADE with similar software and services

Software	Pros	Cons	Compared with COMRADE
ArbiMed Inventory (Arbimed, n.d.)	• Digitalized inventory management system. • Predictive inventory system to know the usage. • Can purchase inventory directly from system. • Statistical analysis available.	• Different Application for Different medical sector • Different Purchase is required for individual medical sector	• Do not provide patient management • Do not provide patient medical report management • Do not provide crowdsourcing facility.
mymediset (Mymediset, n.d.)	• Digitalized inventory management • Can be integrated with the current SAP/ ECC/S4 HANA • Provide inventory purchase and entire supply chain for it. • Statistical analysis of inventory	• Only focuses on inventory and it items.	• Do not provide patient management • Do not provide patient medical report management • Do not provide crowdsourcing facility.
HYBRENT (Hybrent, n.d.)	• Inventory items distribution chain • Provide services to high end hospital as well as local doctors • Provide inventory management option	• Only focuses on inventory and it items.	• Do not provide patient management • Do not provide patient medical report management • Do not provide crowdsourcing facility.
SURGICARE (SurgiCare,)	• Robust inventory management system • Can manage inventory across different facilities. • Cross browser webapp • Give analytics of inventory used monthly.	• Only focuses on inventory and it items. • No Mobile application.	• Do not provide patient management • Do not provide patient medical report management • Do not provide crowdsourcing facility.
Chetu (Chetu,)	• Digitalized Patient records. • Available for both patient and doctors • Provide health care analytics • Can book appointments from app.	• Only focus on patient health management • Do not have provision for any predictive analysis for future use	• Do not have inventory management • Do not provide crowdsourcing facility • Do not provide inventory consumption prediction.
VALUECODERS (Valuecoders, n.d.)	• Digitalized records of patient • Remote telecommunication facility in emergency case • Real time analytics for better health management	• No inventory management • Do not have provision for any predictive analysis for future use	• Do not have inventory management • Do not provide crowdsourcing facility • No digital history records for patient medical reports • Do not provide inventory consumption prediction.
PixelCrayons (pixelcrayonsTM, n.d.)	• Health tracker • Automated diagnosis based on symptoms • Can track water and food intake along with calorie counts	• Do not provide any medicine recommendation or management • Basic automated app with no professional manual interference	• Do not provide digitalized record history of patient, report or inventory • Do not provide crowdsourcing facility • Do not provide inventory consumption prediction.

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As there is no direct platform that compares functionalities we discussed in the paper, so we will offer a comparison of software solutions at individual modules. ArbiMed Inventory, mymediset, HYBRENT, SURGICARE are all well known and most used inventory management system specially designed for hospitals and clinics. Systems like ArbiMed Inventory and mymediset provide options to purchase medical supplies from their application itself as they are linked with resource suppliers as well. This feature is not available in our proposed approach but such application are not free. Our current approach is a free to use cross platform application which can be used by any department of medicine as long as they are registered and verified on the platform. Like the other software out approach to provide a predictive analysis in inventory consumption and on top of it also notify if any resource required is not sufficiently stocked or out of stock. The proposed approach also keep the historical records of the resources and which patient they were appointed to and when they were appointed which none of the above mentioned software provides.

Applications like Chetu and VALUECODERS are some of the well-known patient management applications out there. They provide all the necessary details required for the patient and doctors. But they do not keep historic records of the patient. Our proposed approach not only just keep historic records of the patient but also keep other reports records like pathology test records and radiology test records and other medical history and vital records. Over all there are few features that are available in the above application which are good and useful but our approach also has some distinct features which are more dynamic and new to the medical technology.

The University of Cambridge (University of Cambridge, 2020) developed the proof of concept to predict the impact on resource needs (ventilators, ICU beds, etc.) due to Covid-19. According to the survey carried out by the authors, to date, there has been no citation of any complete system like the proposed approach used for resource optimisation in the Indian context.

Though the present work is one of the attempts to forecast the demand of ICU collaboratively, the study also documents challenges like reaching out to collaborators for the intended purpose and selecting appropriate machine learning-based (ML) algorithms from a range of ML algorithms managing heterogeneous data point. But CPAS (Qian et al., 2021) is one step forwards towards collaborative resource sharing for effective capacity planning.

As the current pandemic is spanning over a year, the related studies have been published to share contemporary approaches and innovative solutions adapted to mitigate challenges elevated during the Covid-19 spread.

In the current proposal, the authors wish to extend the concept of Crowdsourcing for resource optimisation. Recently, the researchers started evaluating the concept of Crowdsourcing in healthcare (Wang et al., 2020; Wazny, 2018). Broadly, Crowdsourcing's trend in healthcare is for sharing content for experimental/clinical studies going on related health domain. But no active attempt is observed to explore the possibility of crowdsourcing hospital resources for effective and efficient healthcare management.

Thus, in conclusion, the proposed solution aims to help hospitals better manage patient data and resource management. Also, develop a prediction model based upon the patient's condition to predict the further resources requirement.

Proposed Approach

In line with the present chapter's concept where authors proposed a digitised hospital management system, in work (Gholamzadeh et al., 2021), authors presented a framework using medical informatics. The

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objective of the proposed framework was to manage the sudden emergence of epidemics or pandemics. The framework consisted of layers like clinical layer, logic layer, research and management layer and user interface. Each layer had its own modules. The user interface is offered for patient reports, alert and recommendation notifications, Clinical planning, and patient record management. The framework intended to integrate data from different resources like data from various hospitals, research data. The framework had epidemiological modules to study and observe patterns resulting in an epidemic. The authors mentioned that the approach adopted to propose a framework was detailed research on medical informatics. The next step to validate the analysis and proposed framework was to conduct a focus group survey. Thus the medical informatics could offer different insights to strengthen the existing health infrastructure.

The proposed solution aims to attempt the healthcare infrastructure to manage the peak requirement of hospital resources. The proposed work considers the current pandemic to outline the healthcare facility's objectives to offer adequate health services.

- Interactive and Intelligent Module of patient data
- The algorithmic approach to predict the utilisation of medical resources
- Crowdsourcing facility among participating hospitals to share resources among themselves

The major modules of proposed solutions are Patient Data Management, Inventory Management, and Crowdsourcing Dashboard. The Options to add and edit the patients and patient reports accessibility on a single click for the doctors are features of patient data management. The module will be strengthened to map the patient data points with diagnosed diseases to maintain patient trend towards recovery or extended medical treatment. The prediction of reaching the existing health care setup's capacity takes the patient tracker unit's input. Further, the current healthcare setup can support by utilising the crowdsourcing approach. The crowdsourcing feature is enabled only among the hospitals in the nearby vicinity and ready to share resources or within the same healthcare infrastructure management hospitals.

Figure 1 shows the dashboard of the proposed hospital management system. The dashboard captures gender and age-wise variation among admitted patients. Also, the dashboard has the visualisation of bed occupancy status within the hospital over the period. Amongst other things it also shows various visualisation that appears on the dashboard to present cumulative information about admitted patients at a glance.

Patient and Report Monitoring

A proposed setup includes a patient monitoring platform that keeps track of patient data and reports. The various information related to the patient could upload in the respective tab. The attributes of a presented module are:

- An interface to interact with patient data or report data.
- Mapping individual patients to respective report data.

Figure 2 captures shows the interface where the user can interact with various patient details like patient personal details, Inventory utilized, pathology reports, bed allocations and more.

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Figure 1. Data visualisation of various data related to patient



Figure 2. Interface to interact with patient information



Figure 3 captures the glimpses of the user interface of the proposed system, which captures the user information at a glance.

As shown in Figure 4, the inventory issue history collects the medication issued to patients assuming some of the medicines given from the hospital's inventory.

Figure 5 depicts the interface to search Pathology and Radiology reports. The interface is designed such that the related reports can search for individual patents or by types of test.

The detailed description of tests entered in the digital interface—the sample of one of the radiology reports in the digitised form given in Figure 6.

Figure 7 shows the data storage approach developed for the patient module designed to handle the data.

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Figure 3. Patient's information in digital form

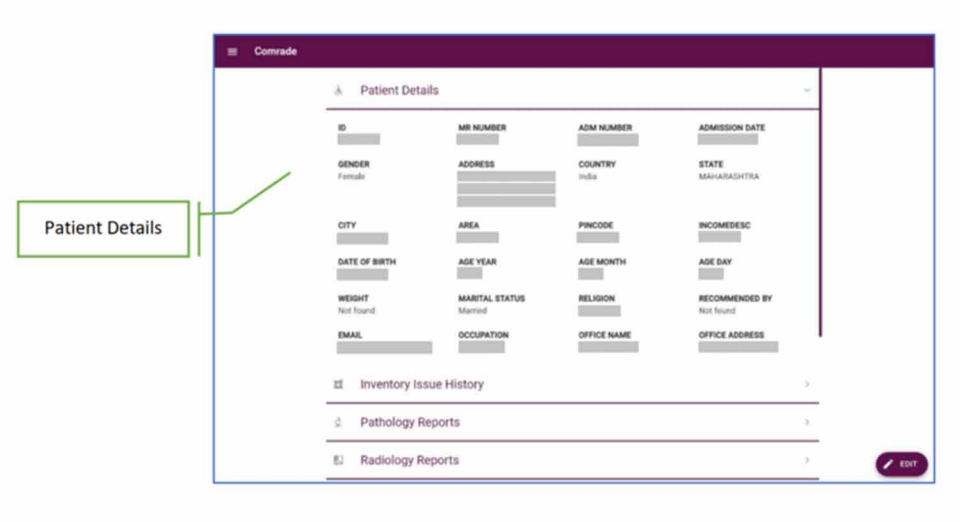


Figure 4. Inventory issue history interface

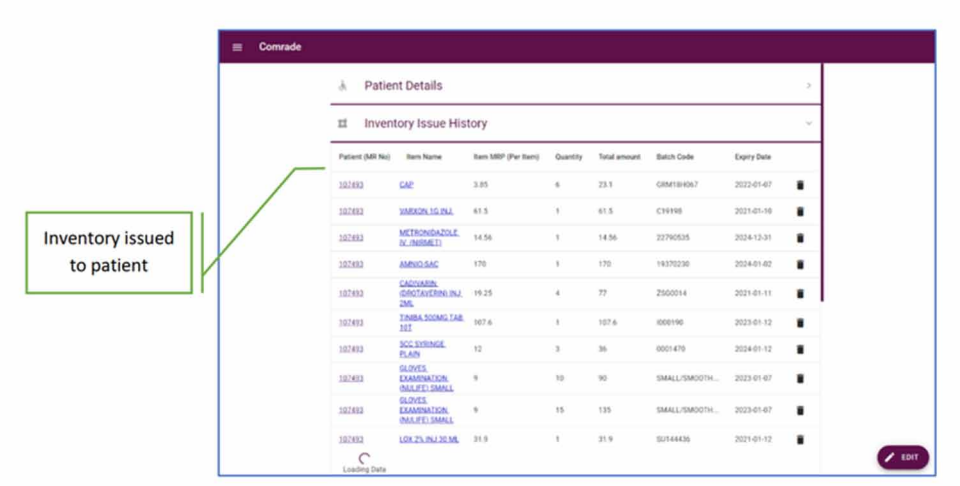
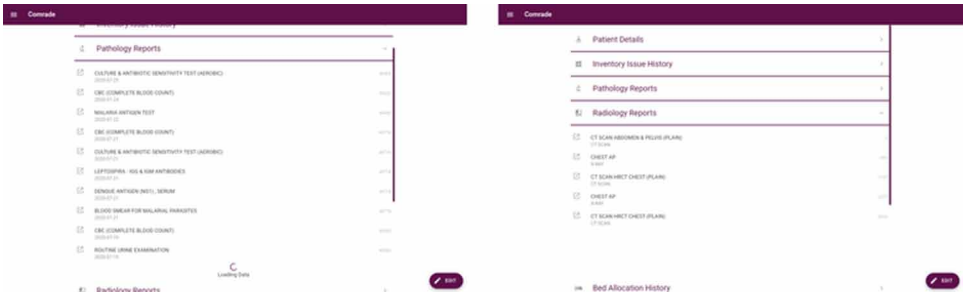


Figure 5. Pathology and Radiology interface for patient



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Figure 6. Digitised Radiology report

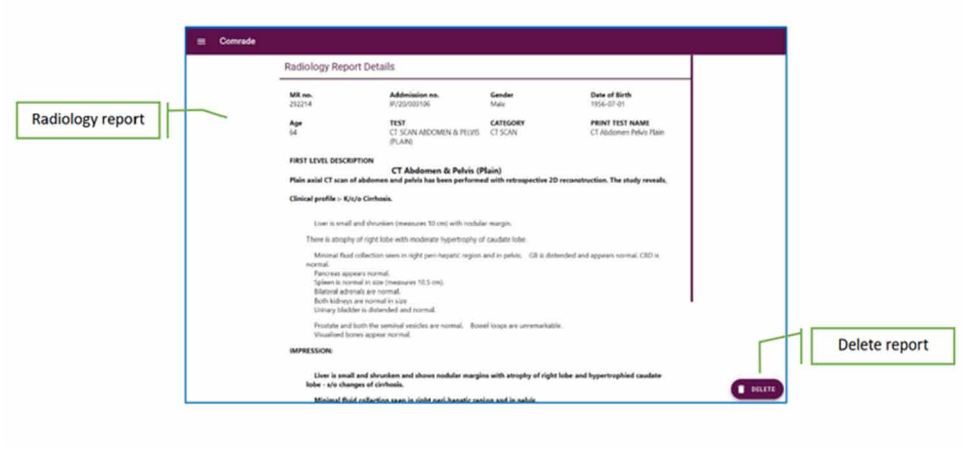
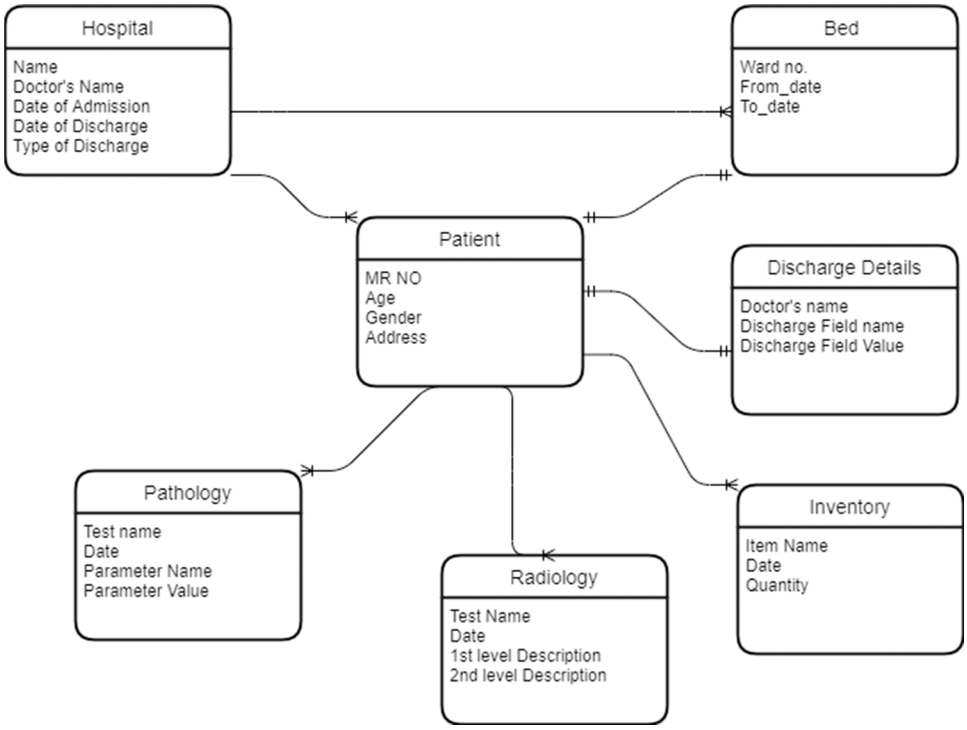


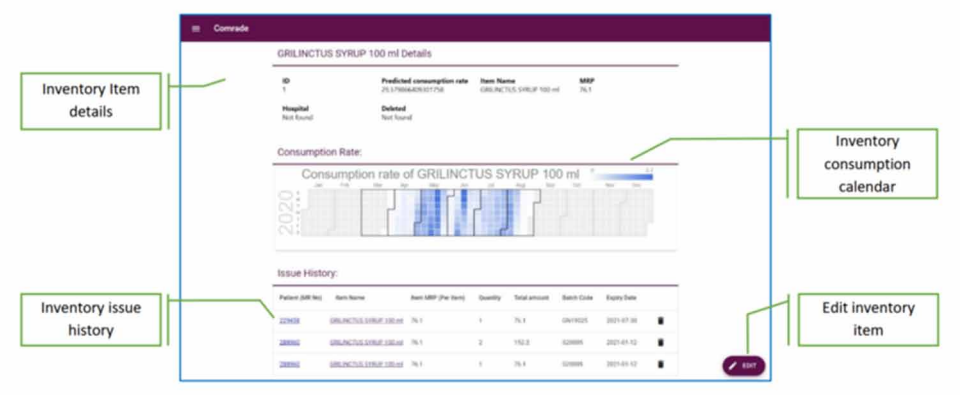
Figure 7. Data storage approach for patient and report monitoring module



The monitoring module captures essential parameters useful in crowdsourcing hospital resources, i.e. bed occupancy, medicine inventory. The bed occupancy monitors and display on the dashboard in the hospital management system. Figure 8 shows the display of how the consumption of medicine is monitored on the proposed platform.

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Figure 8. Monitoring consumption of medicine



The present chapter offers a review of existing commercial software used by hospitals. The medical inventory software was a separate part of hospital management. The current chapter lists down a few of the software recognised in the healthcare industry for inventory management. The solutions like mymediset (Mymediset, n.d.), ArbiMed Inventory (Arbimed, n.d.), Sortly (Sortly,), Hybrent (Hybrent, n.d.), Surgicare (SurgiCare,) are used for efficient and intelligent inventory management. The solutions are up to date with technology support like cloud computing-based solutions, but none of the solutions implements prediction of the requirement of inventory. Thus, proposed solution aims Recurrent Neural Network (RNN) based prediction model is used for inventory prediction.

The Algorithmic Approach to Predict the Utilisation of Medical Resources

The entire data regarding a patient is digitalised using the proposed system. As a result, it is easy to analyse data and apply some AI techniques to make patient care more convenient. The discussed approach targets implementing inventory management supported by an innovative artificial intelligence (AI) monitoring how commodities are being consumed.

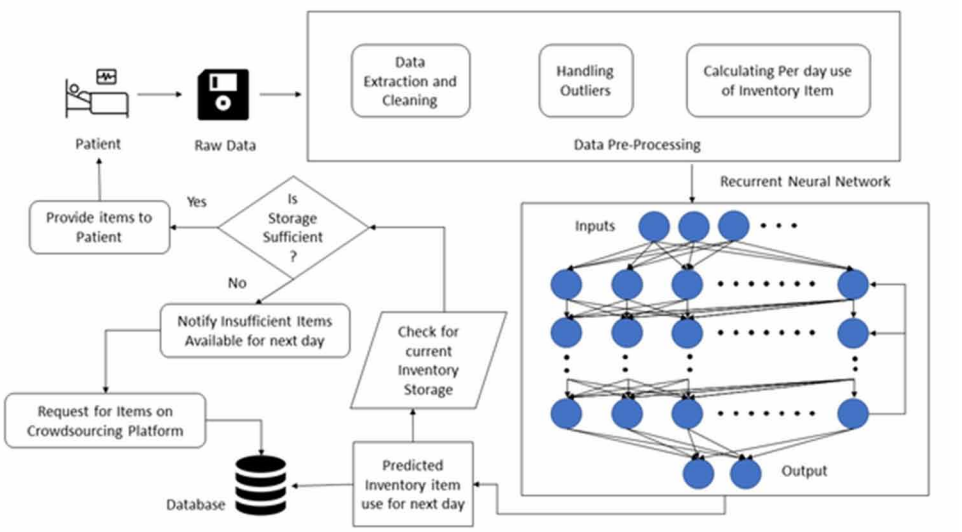
As shown in figure 9, the proposed approach uses a Recurrent Neural Network (RNN) based prediction model to find the medical resources' consumption rate and predict these resources' requirement for the future. An RNN model is trained based on the current consumption of the resources. This model calculates the total consumption of the resource in the entire hospital daily and updates itself for better results.

The trends of item consumption for five consecutive days are provided as input to the model. These trends also contain the aggregates like average Age, number of patients in a particular ward, Number of Patients in a specific ward etc. The aim was to have data points which might help the model distinguish between the type of patients. For example, with an increase in the number of patients admitted to gynaecology and obstetrics departments, the inventory items that are required for the nursing of a baby might come in high demand.

As output, the model will provide the rate of consumption of the inventory items for the day. If the stock in the inventory for that item is less than the predicted consumption rate, the hospital can initiate a purchase.

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Figure 9. A RNN based approach for predicting medical resources' consumption rate



An RNN was preferred over a multilayered neural net as RNN are better at predicting time series related data. RNN helps us provide sequential data (here daily consumption rates), stored as a hidden state after each step, giving it a sort of memory or feedback of previous inputs/ output. This makes it ideal for inventory-based decision making.

Crowdsourcing Facility Among Participating Hospitals to Share Resources

As it is established that the severely infected Covid-19 patients' sufferers from hypoxic respiratory failure, such patients require ventilator support.

The report (Halpern & Tan, 2020) generated on May 2020 by the Society of Critical Care Medicine (SCCM) compiled the data and estimates on ICU, occupied ICU beds, number of engaged and available ventilators. The report also confirmed the connectedness among ICU resources – ICU beds, supporting equipment, trained staff. Thus in the case of resource sharing, the ICU staff could also be considered.

In work (Phua et al., 2020), the role of ICU communities to undertake discussed in detail. The study outlined challenges in front of the ICU community to manage critically infected Covid-19 patients. Recommendations suggested by researchers include optimisation of workflow, increase in an ICU care facility, collaborative efforts at a different level in terms of sharing of data that is authenticated, following ethical practices in treatment and sharing resources. The discussion in (Halpern & Miller, 2020) presented views on why it is not beneficial to increase the production of ICU resources, such as an increase in the supply of ICU beds in response to demand for them. The study stated that ICU capacity is at the US's optimal level though it has proven insufficient in the current pandemic. But investing money in building up the capacity of ICU infrastructure would futile once the pandemic is over. Thus, it is recommended to invest money with other much needed outcome in response to the pandemic. In agreement with the preceding study's views, the (Parker et al., 2020) supports the claim that hospital resources creation is not an optimal solution, whereas redistributing the resources among facilities will result in a better outcome.

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Thus the proposed approach is motivated to present the concept of Crowdsourcing to share hospital resources. Algorithm 1 captures the algorithmic approach applied to apply the Crowdsourcing concept to share hospital resources

Algorithm 1: Algorithmic approach to applying Crowdsourcing to share hospital resources

```
1. Start
2. Let H be a hospital registering to crowdsourcing platoform
3. Let A_p be the platform admins and A_h be the hospital admins
4. A_p will verify the details of H from legitimacy
5. If H is verified successfully:
        H can assign A_h for itself with proper senior designation
        If count of A_h for H < 4:
             A_h status will be assigned
        else:
             A_h position is already assigned
        End if

        let new member registration for H be M
        Randomly select any A_h that will verify details of M for legitimacy
        if M is verified successfully:
             Account for M is activated
        else:
             Account for M is not activated
        end if

        let B be required bed and I be required inventory item
        let T_b and T_i be threshold values for bed and inventory item
        if the item required is B:
                check for availability for B
                if count of B > T_b:
                     Allow sharing of B
                else:
                     Do not allow sharing of B
                end if
         else if the item required is I:
                check for availability for I
                if count of I > T_i:
                     Allow sharing of I
                else:
                     Do not allow sharing of I
                end if
         else:
               Invalid option
```


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```
          end if
6. else:
         H will not be a part of crowdsourcing platform
7. end if
8. stop
```

Any registered hospital on the proposed platform can make use of Crowdsourcing. It is a feature that can be used to share necessary items and a hospital bed with other registered hospitals. All the hospitals have four special accounts, which are called Hospital Admins (HA). These accounts can monitor activities that their hospital members perform. HA also have special rights in Crowdsourcing. Every hospital is assigned a threshold value of Items and bed by default, and the HA can modify these default values. Also, these threshold values determine if the hospital can share resources with other hospitals. As a hospital finds out there is a shortage of resources; the hospital can request other hospitals for required resources. These requests will be visible to all the hospital registered on the proposed Crowdsourcing. Also, a priority request option is available to send request priority request to the nearby hospital. Based on the travel time calculated using an external API, the proposed Crowdsourcing finds out the nearby hospital for these priority requests. Once the request is live on the proposed Crowdsourcing, any hospital with resources greater than the threshold value can accept the request and share their resources. The proposed Crowdsourcing check for the currently available resources in the inventory of the hospital. If the requested item count is greater than the HA's threshold value, the hospital can choose to share a minimum one and maximum of the total requested item with the other hospital. Once the hospital agrees to share the resource, the donor hospital can send out an ambulance to deliver the resource if the resource is a medical item. If the resource is bed-based, the patient can be relocated to the donor hospital.

The user interface on interactive hospital management for Crowdsourcing is presented in figure 10 and figure 11. The interface offers the resources offered on the Crowdsourcing platform. To illustrate the concept, two resources, medicine inventory and bed, are included on the interface. Figure 12 depicts the way HA can request resources from nearby hospitals.

Future Scope

Day by day, technologies similar to the Internet of Things (IoT) become mature, and the health domain is one to garner the IoT technologies' benefits. Though technologies like IoT, AI assures connectedness and preparedness of health services, it will be equally crucial to managing the emergency by extending the facility to share resources.

Crowdsourcing among healthcare facilities is a revolutionary approach in the health domain. The proposed solution can amalgamate all required functionalities, such as digital records of patient data and medical inventory. Also, the physical status of hospital infrastructure is captured along with inventory status. The proposed solution can be implemented in hospital infrastructure as preceding unit to inventory management software. The consumption interface triggers the need for inventory update. The related inventory management software employed by the hospital could satisfy the procedure to acquire predicted medical inventory.

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Figure 10. Resources offered on the Crowdsourcing platform

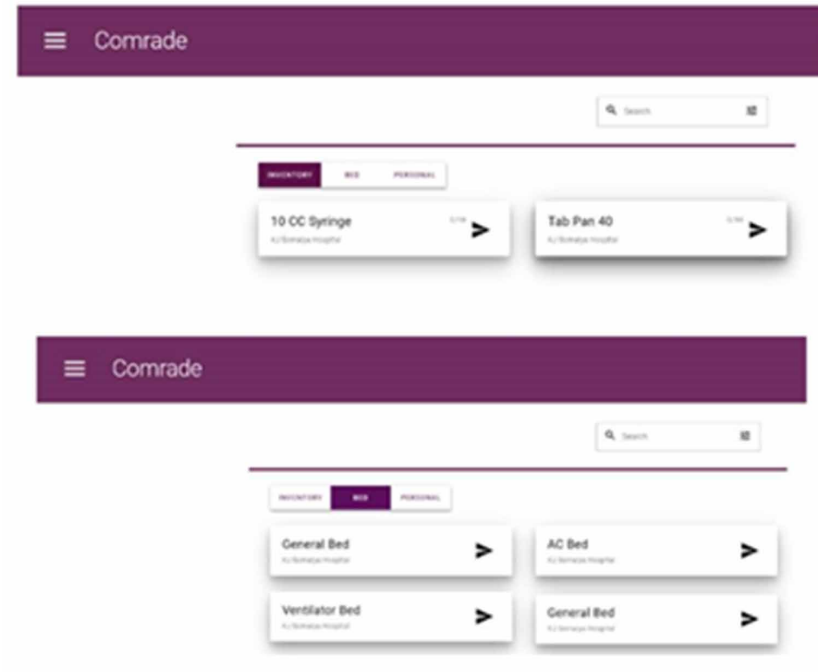
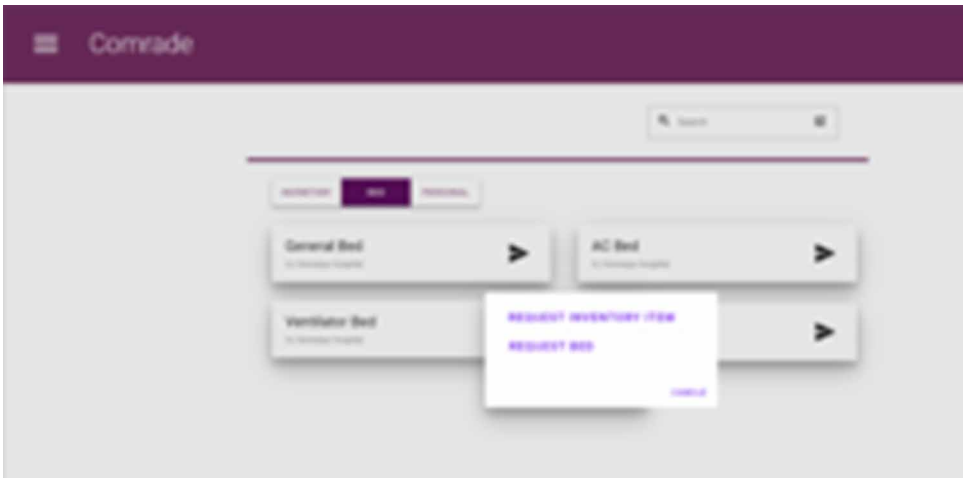


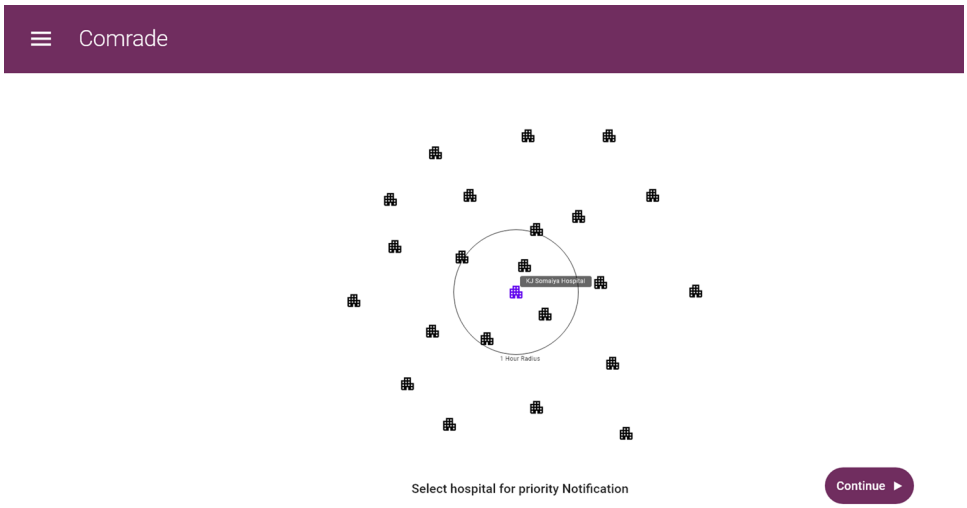
Figure 11. HA can request resources from nearby hospitals



The Crowdsourcing platform implemented with Blockchain technology will be the future scope of the proposed work. The strength of Blockchain technology is immutable and trustworthy records. Also, Blockchain-based Crowdsourcing implementation is coming up as an aspiring solution in the different sectors of industry. Thus, the proposed solution can be implemented with Blockchain to make communication evolving request and response among the hospitals were trustworthy and immutable.

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Figure 12. HA can select hospitals from the nearby vicinity



CONCLUSION

The global Covid-19 pandemic has directed an unprecedented load on hospitals worldwide. Under the lockdown standpoint, upscaling the medical resources is a challenge. And this challenge only gets amplified with each wave the pandemic has over the country. To handle this imbalance to the best of capacity, hospitals need a good management system. This obvious necessity is amiss from the majority of the hospitals, especially the government hospitals. Development of a tool to make such a system available to the hospital aims for Crowdsourcing-based Optimisation of Medical Resources Attending Demand Equalisation. The proposed solution is an ML-based informed intervention for Covid-19 treatment to allow hospitals to manage resources more efficiently.

In summary, the proposed system predicts the future inventory requirements. The proposed work offers the novelty of extending the crowdsourcing concept in sharing resources among the hospitals. The insights provided by the solution will benefit the organisation involved in the treatment and management of Covid-19 patient as follows: Prediction of the utilisation of the available resource. Hospitals can ask for support in terms of medical resources from the partnered organisation, and medical care centres can share the resources per their utilisation.

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Chapter 18
Prediction and Recommendation System for Diabetes Using Machine Learning Models

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ABSTRACT

Diabetes is one of the most deadly diseases on the planet. It is also a cause of a variety of illnesses, such as coronary artery disease, blindness, and urinary organ disease. In this situation, the patient must visit a medical center to obtain their results following consultation. Finding the right combination of characteristics and machine learning techniques for classification is also very critical. However, with the advancement of machine learning techniques, we now have the potential to find a solution to the current problem. The healthcare recommendation system (HRS) may be designed to predict health by evaluating patient lifestyle, physical health, mental health aspects using machine learning. For example, training the model using people's age and diabetes helps to predict new patients without a specific diagnostic for diabetes. The proposed deep learning model with convolutional neural network (D-CNN) achieves an overall accuracy of 96.25%. D-CNN is found to be more successful for diabetes prediction than other machine learning (ML) approaches in the experimental analysis.

1. INTRODUCTION

Speedy, economic data output and computational research into the Big Data field is constantly driven by significant breakthroughs in biotechnological and, more significantly, high-performing information technology. The major purpose is to analyze the expanding amount of biotic data and to provide a

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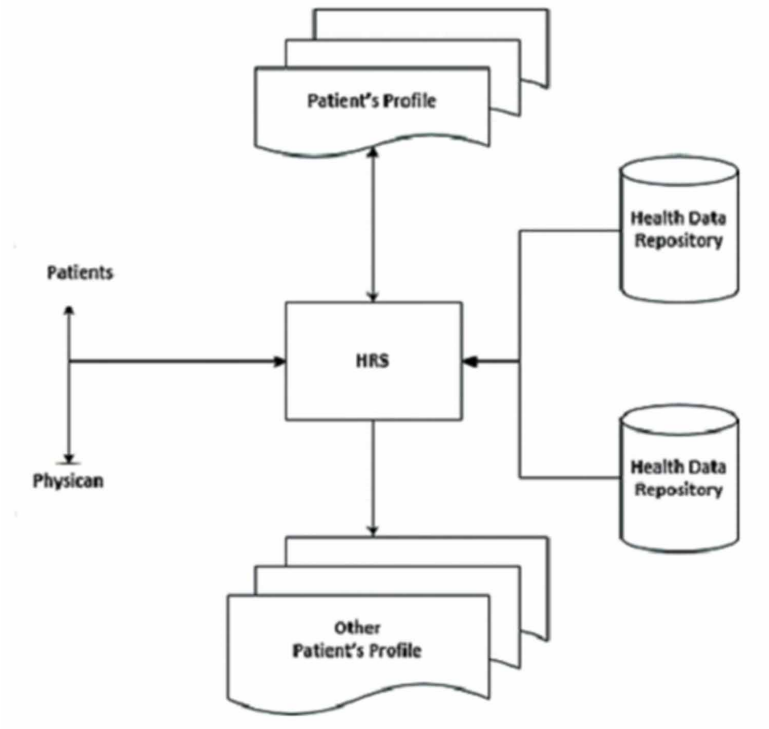
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framework for improving responses to fundamental medical and biological queries. The ability of the correct methodologies to recognize forms and model building from data determines the efficiency and reliability of these procedures. Human-threatening disease prognosis and therapy are some of the most important scientific applications. One such ailment is Diabetes Mellitus (DM).

A medical practitioner can manually diagnose DM or use automatic equipment to do so. Any of these methods of DM measurement has advantages and disadvantages. The key advantage of manual diagnosis is that the DM detection technique does not require the assistance of a machine, allowing the medical expert to specialize in the field. Even an experienced doctor may be unable to properly diagnose the symptoms of DM in its early stages. To resolve these shortcomings, medical recommendation systems should help people and physicians take better healthcare decisions (Tran et al, 2020). The recommender systems have been applied in online dealers, streaming services, and social networks to facilitate the choosing process for consumers. These systems were recently widely implemented in the healthcare sector to better support medical ideas. HRS gives a higher degree of personalization, increases the intricacies of the advice made, and enhances the users' understanding about their health, as do its forerunners in this field (e.g., medical specialist systems). HRS priorities are to ensure that patients receive the relevant information at the right time while guaranteeing accuracy, dependability, and data protection. In addition, these technologies are designed to lower healthcare decision-making costs (in terms of time and effort). The block diagram of HRS is shown in Fig. 1.

Figure 1. Health Recommender Systems – HRS Block Diagram



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Due to progress in machine learning (ML) and Artificial Intelligence (AI), automated detection of disease and diagnosis are more likely and effective at an early stage than manual recognition of DM (Jyotismita et al, 2020). The DM field generates large amounts of data based on laboratory evaluations, patient reports, treatment, follow-ups, and medicine, among other things. Manually assembling all of the data is a challenging task. Because of ineffective data management, the quality of data organization has suffered. Increased data volume necessitates a more efficient and effective technique to extract and analyze data. In current and new hospitals, data collecting and inspection machines are hired to enable data collection and sharing in large information systems. When compared to manual detection and diagnosis, an automated device can detect DM and treat problems with significantly more ease and dependability.

Each ML and AI method has its own set of advantages and disadvantages. As a result, both strategies have been employed to create automatic DM detection systems. For AI and ML systems to operate as humans, they require ability and clarity (Jyotismita et al, 2020), because many of the most successful Ml and AI technologies are the least transparent. The ability to explain oneself via AI systems encourages doctors to have more confidence in future AI systems. The causability is based on a causal model which is assessed in terms of efficiency, effective causal understanding, and user transparency.

In recent years, several researchers ((Jyotismita et al, 2020, Kavakiotis et al, 2017) have applied machine learning and artificial intelligence (AI) technologies for DM control, self-management, and customization. To extract insights from the diverse data of the patients, data-driven technologies such as machine learning can be used. The proposed system generates personalized recommendations based on previous learning experiences and clinical data patterns. For medical database classification and prediction of diabetes risk levels, Deep Learning and Convolutional Neural Networks are utilized.

1.1 Contribution of the Paper

The contributions of this paper are (1) Investigation of machine learning and artificial intelligence-based techniques to DM detection, treatment, self-management, and personalization, (2) Using Deep Learning and Convolutional Neural Networks, design and develop a machine learning model for diabetic health recommendation, (3) Experimental Analysis of the proposed system

1.2 Organization of the Paper

The following is how the paper is structured: Section 1 gives a brief overview of the DM and HRS, Section 2 discusses the research methods used in this field, Section 3 describes the proposed methodology, Section 4 presents the experimental setup and analysis, and Section 5 discusses the proposed model's future scopes and challenges followed by the conclusion.

2. RELATED WORK

The results are based on a range of healthcare data sets and analyses and predictions using various methodologies and approaches. A range of prediction models has been developed and deployed by researchers through technology, machine learning, or combinations of data mining approaches.

Several technologies have recently been applied to forecast diabetes, including the Support Vector Machine (SVM), the Decision Tree (DT), logistical regression, and others (Kavakiotis et al, 2017). The

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paper (Polat et al, 2007) has been utilized to differentiate diabetics from healthy persons through Principal Component Analysis (PCA) and neuronal fuzzy inference. The study (Yue et al, 2008) employed the Quantum Particle Swarm Optimization (QPSO) algorithm of the weighted least-squares support vector machine (WLS-SVM) to predict type-2 diabetes. LDA-MWSVM is the method proposed in the study for the prediction of diabetes (Duygy and Esin, 2011). The researchers used Linear Discriminant Analysis to minimize the dimensions and extract features of this system (LDA). In paper (Razavian et al, 2015) logistic regression-based prediction models have been developed for the treatment of high-dimensional datasets for different types of type 2 diabetes datasets. Research (Georga et al, 2013) focused on glucose and used SVR as a multivariate diabetes prediction regression issue. In addition, other types of studies have used ensemble techniques to enhance accuracy (Kavakiotis et al, 2017). The article (Ozcift and Gulten, 2011) developed a new rotational forest strategy that includes 30 approaches to machine learning. The research (Han et al, 2015) proposed an algorithm for machine learning, which changed the SVM rules of prediction.

To predict diabetes mellitus, the researchers (Zou et al, 2018) have employed decision trees, random forests, and neural networks. The principal component analysis (PCA) and minimum redundancy maximum relevance (mRMR) in this study have been used to minimize dimensionality in this work. When all of the criteria were employed, the findings indicated that random forest prediction had the highest accuracy. This paper (Gadadharan et al, 2019) offered a Random Forest diabetes algorithm to create a scheme that can use the Random Forest algorithm in machine learning technology for early diabetes prediction of a patient with more precision. The model proposed produced the best results for diabetic predictions, demonstrated that the prediction system is capable of predicting diabetes disease accurately and efficiently instantly. Diabetes prediction: (Nonso et al, 2018) a supervised learning approach has been described. Five widely used classifiers were used for the assemblies and their performance was added using a meta-classifier.

The goal is to forecast diabetes through the use of machine learning techniques employing three different supervision methods, including SVM, logistic regulation, and ANN. This study provides a mechanism for the earlier detection of diabetes. The study (Shetty et al, 2017) has suggested diabetic disease prediction using data mining build Intelligent Diabetes Disease Prediction System that provides analysis of diabetes malady using a database of diabetes patients. In this technique, it is suggested that you use Bayesian and K- Nearest Neighbor (KNN) algorithms to a diabetes patient database and that many variables of diabetes be used to predict it. Six distinct algorithms have been used in the study (Sarwar et al, 2018). The performance and precision of the algorithms used are examined and contrasted. A comparison of the various methodologies of machine learning shows which algorithm is most suitable for the prediction of diabetes.

To identify and classify, the paper (Mokdara et al, 2018) has used various types of KNN (K-Nearest Neighbor) algorithms. The database was built according to the American Diabetes Association's guidelines. The learner classifier approach analyses the output using 4900 samples at the training stage. Following then, 100 data samples are used in the test. The results show that the KNN types (Fine, Medium, Weighted, and Cubic) outperform the Coarse and Cosine approaches in terms of precision. The accuracy with which samples are classified is known to be the most relevant for Fine KNN. The paper uses Machine Learning algorithms (Ali et al, 2020) to build a prediction framework for diabetes based on Iridology or iris. The created framework includes ways for creating ocular pictures as well as image processing algorithms. The Iriscope Iris Analyzer Iridology system is used to capture iris images. To obtain the

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textural properties of the image, the Gray Level Co-Occurrence Matrix (GLCM) technique is used for feature extraction. To discriminate between nondiabetic and diabetic groups, the KNN method is used.

Type-I Glycemia must be controlled with exogenic insulin management as diabetes is a symptom of a chronic metabolic illness caused by autoimmune damage by cells of the beta pancreas. The paper (Aminah and Saputro, 2020) offered a system for estimating postprandial glucose profile by using several KNN classifications, using minimal therapy, and indicating alterations in the amount of time and/or food bolus. The paper (Sneha and Gangil, 2019) has proposed a method that focuses on the selection of parameters associated with early diabetes detection using a predictive model. They used a sample Diabetes dataset (2500 data items) from the UCI machine repository with 15 attributes. Only 11 features identified by the suggested technique are used in the experiments. The results show that the Naive Bayes test has the highest accuracy of 82.30 percent. To improve the precision of the categorization, research frequently simplifies the selection of appropriate sample qualities. The risk of diabetes in patients was determined by ontology and machine learning algorithms (Lakshmi et al, 2019). Also, the risk level options are established with the Naive Bayes algorithm, which serves to make medical record decisions. In the suggested algorithm the parameters confusion matrix, accuracy, and mean are examined, and this study is considered as having a greater accuracy level than prior studies.

The paper (Qomariah et al, 2019) suggested a method to extract and categorize attributes by SVM. The authors utilized the high-level functions of the last connected layer, which focused on transfer learning from the Convolutional Neural Networks, as the input for classification using the SVM. Based on test results, the highest accuracy levels are, respectively, 95.24% and 95.83% for base 13 and base 12. The research identifies the application of simple diabetic toenail analyses using ML approaches to thoroughly identify type II diabetes (Carter et al, 2018). In Toenails, there is little difference between the amounts of Cs, Aluminum, V, Ni, and Zn between healthy people and type II diabetics. Twenty-two-part toenail concentrations are then analyzed using seven different ML algorithms to provide a non-invasive diagnostic procedure, together with personal data such as gender, age, or history of smoking. The LDA is used as a classification.

Neural Networks (NN) is a non-linear approach that is commonly utilized as a Deep Learning model (Larabi et al, 2019) for the identification and diagnosis of diabetes mellitus. NN is made up of a large number of highly interconnected processing elements called neurons that work together to solve any problem involving diabetes data. Neurons are designed for certain applications connected to Diabetes detection since they can extract significant information from a large set of data. In the studies that were chosen, UC methods were utilized numerous times. Using glucose and insulin, the paper (Severeyn et al, 2019) has employed the k-means clustering approach to categorize samples with type-II DM and pre-diabetes. During the oral glucose tolerance test, a database of 188 samples with insulin and glucose readings is used. For glucose, the k-means clustering produced is more than 0.6 (silhouette coefficient).

Machine learning approaches are commonly employed in diabetes prediction, and they produce better outcomes. When trained, Deep Learning algorithms extract feature data and learn indirect features that can distinguish between large volumes of Diabetes data. To predict a patient's diabetic risk level, we used deep learning using Convolutional Neural Networks in this study.

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3. PROPOSED METHODOLOGY

The Recommender System (RS) is a system that predicts diseases and makes therapy recommendations. To generate forecasts and recommendations, the RS system requires input data. Diabetes data will be used as a case study in this study. Diabetes is a chronic condition or collection of metabolic diseases in which a person has an elevated blood glucose level in the body due to insufficient insulin synthesis or improper insulin response by the body's cells. Type 1, type 2, gestational diabetes, and pre-diabetes are the four forms of diabetes (Larabi et al, 2019). All of these facts, as well as the serious repercussions of diabetes, inspired us to create a system that may help people forecast the likelihood of developing diabetes using basic medical data and provide suitable diabetes management suggestions. Because if a person is aware that he or she may be a diabetic patient at an early stage, he or she may be able to control the severity of the disease by following the advice. He will also be warned ahead of time and will allow himself to be thoroughly diagnosed. In the next sections, the proposed methods for both systems are stated.

3.1 Diabetic Prediction Using AI

In the first section of this section, a strategy for developing a diabetes prediction system utilizing deep learning is proposed. Eight diabetes-related risk factors were utilized as independent variables to determine the dependent variable's estimated risk. Deep Learning (DL) has been achieved using a Convolutional Neural Network (CNN).

CNN is one of the deep learning algorithms of study most commonly utilized. It is a type that uses many layers of perception sequentially linked to an artificial neural network. Before changing CNNs into the required output, the input and a sequence of operations take place on it. This output can be utilized for feeding in the following block from the previous levels. The three main types of layers in CNN, represented in Figure 2 are revolutionary layers, bundling layers, and fully connected layers. The core of the network is the coevolutionary layer with local connections and shared property weights. The aim is to learn the characteristics of input data. The input function mappings are first composed of a kernel and then the results are supplied via a non-linear activation function. The bonding layer might be seen as a fuzzy filter because it minimizes the dimension while enhancing the robustness of the characteristics. Finally, the fully connected layer is sent to every neuron in the system by receiving signals from preceding levels. This classification is carried out on the output layer, which is usually a softmax classifier.

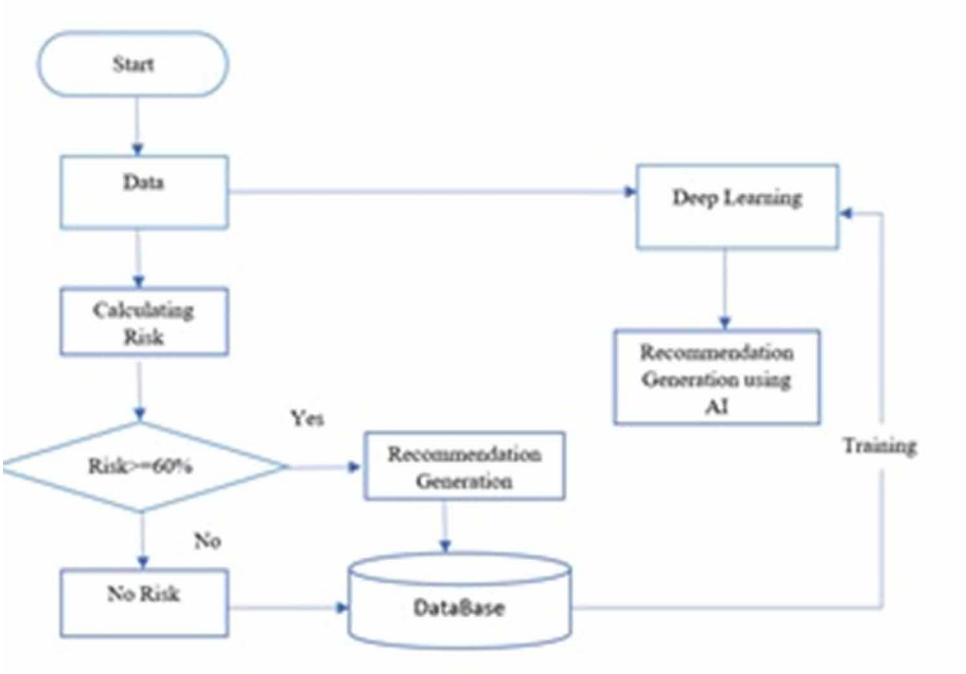
Figure 2. Architecture of the Proposed CNN Model



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At first, the dataset has been cleaned by removing the null and infinite values. From the cleaned dataset, the highly weighted attributes have been identified. In the next step, the dataset has been prepared for the training and testing process. Then, the dataset has been trained by the DL model for prediction. If the prediction yields unacceptable results, the algorithm must be retrained by preparing the dataset for the training and testing procedure. And if appropriate findings are obtained, the desired result will be realized as shown in Figure 3.

Figure 3. Process Diagram of Prediction Model



3.2 Developing a Recommender System based on Predictions

The proposed diabetes prediction system is initially implemented. The recommendation system is then implemented using the predicted risk from the prediction system.

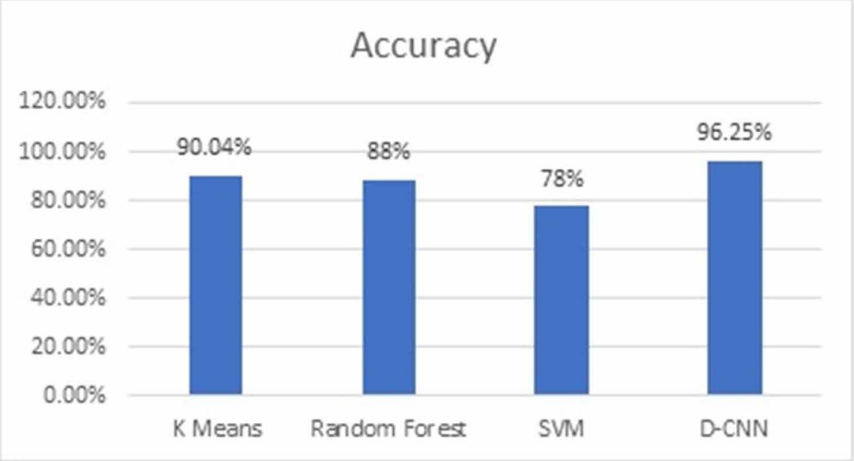
This method computes the diabetic risk level of a patient. A recommendation system has been created that can generate suggestions for patients with a risk percentage of having diabetes greater than or equal to 60 percent. Deep Learning Learning was employed to create this system. As a result, a mechanism for generating suggestions has been developed. The steps followed for the recommendation system are outlined in the flowchart given below in Figure 4.

Steps taken for the proposed method are as follows:

To begin, the risk of diabetes was assessed using the prior system, and the three most important characteristics were identified. Then, if the risk percentage is equal to or greater than 60%, some appropriate recommendations are provided by taking into account the most influencing aspects. However, if the risk percentage is less than 60%, the output will be “No Risk .” The parameter Fasting Blood Sugar is next

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Figure 4. Recommendation System Flow Chart



tested to see if it is one of the three most influencing parameters in this scenario. If you have one of these symptoms, you may have prediabetes. In this case, as well, recommendations have been generated. The outcome is saved in the database in both circumstances. The risk of diabetes was determined after following the provided suggestions for a while, and the suggestions were generated again. The system then compares these new suggestions to those previously saved in the database, and the comparison result is saved. The stored dataset then is utilized to train the recommendation system's reinforcement learning algorithms. Instead of delivering the saved data one by one, it has been supplied as a dataset to efficiently update the Deep Learning system.

4. RESULTS AND DISCUSSION

This section covers data collection and analysis to explore patterns and trends that help to predict and evaluate results.

4.1 Experimental Setup

The approach provided is evaluated on the PIMA Indians diabetes data set (PID) available publicly on the Internet and available through the UCI learning machine library (Larabi et al, 2019). The dataset consists of 768 instances with 8 features in CSV format. 500 nondiabetic individuals are present in this dataset, whereas the remaining 268 are patients with diabetes. The characteristics include pregnant count, glucose concentration, blood pressure diastolic (mm Hg), skin thickening (mm), serum insulin (mu U/ml), body mass index, diabetes pedigree, and age (years). Three data pre-processing processes were employed with Python programming. The missing values are replaced by the average value of the associated attribute. After completing the pre-processing stage, he is ready to be training. The dataset is split into training and testing sets with 10 fold cross-validation.

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4.2 Result Analysis

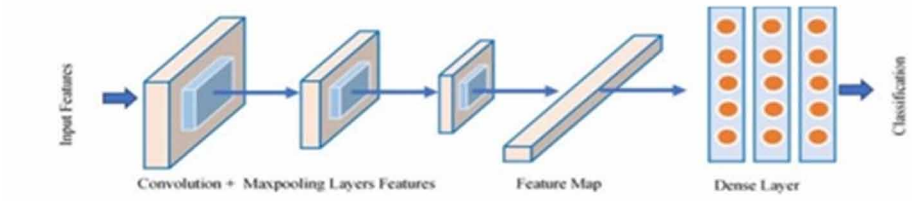
The diabetes prediction has been achieved by using Deep Learning with Convolutional Neural Network on the dataset. Table 1 shows the head of the dataset used.

Table 1. Diabetes Prediction Dataset

Pregnancies	Glucose	Blood Pressure	Skin Thickness	Insulin	BMI	Diabetes Pedigree Function	Age
6	148	72	35	0	33.6	0.627	50
1	85	66	29	0	26.6	0.351	31
8	183	64	0	0	23.3	0.672	32
1	89	66	23	94	28.1	0.167	21
0	137	40	35	168	43.1	2.288	33

The PIMA Dataset (PID) was utilized by several researchers (Larabi et al, 2019; Yahyaoui et al, 2019) to test and train their suggested approaches. Using the same dataset below is a graphical representation of their results and the proposed model in terms of accuracy. For diabetes prediction, Fig. 5 demonstrates the best accuracies attained using several algorithms such as Support Vector Machines (SVM) (Yahyaoui et al, 2019), Randon Forest (RF) (Yahyaoui et al, 2019), KMeans (Larabi et al, 2019), and Deep Learning using CNN (D-CNN), with the suggested approach (D-CNN) achieving the highest accuracy of 96.25%. The D-CNN classifier has an overall accuracy of 96.25 percent, precision of 84.36 percent, recall of 62.74 percent, and f-measure of 70.93 percent.

Figure 5. Accuracies for Diabetes Prediction using PID



After generating the D-CNN model's risk prediction, the risk for each parameter was examined, and the three most affected parameters were determined. Suggestions have been produced based on these parameters. Essentially, it has been attempted to focus on the given clinical parameters and provide recommendations based on the most affected parameters, so that the patient can follow the recommendations and lower the risk percentage.

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5. CONCLUSION AND FUTURE WORK

Diabetes is a long-term illness that can cause its victims to suffer for the rest of their lives. Diabetes cannot be cured after it has been diagnosed. It can, however, be managed. The earlier this disease is detected, the easier it will be to control it. And this system has the potential to be quite useful in this situation. The results showed that D-CNN was more effective for diabetes classification in all rounds of testing, with an overall accuracy of 96.25 percent for diabetic prediction. This system will forecast a person's likelihood of developing diabetes, and if the likelihood is near 60%, the person will be aware of this, and he will be able to adjust his lifestyle choices that influence the likelihood, and he will most likely be able to avoid diabetes. However, if the probability is greater than 60%, the person can consult a doctor and take steps to control the situation before it becomes too late. As Deep Learning can learn vast volumes of unstructured and unlabeled data that even the human brain may take years to understand, in the future deep learning will be paired with multiple algorithms to get improved accuracy. Following the system's previously generated recommendations, it can then generate more suggestions based on the patient's bad or favorable outcome. The clinical histories of patients will be saved from time to time so that the system can make suitable recommendations for the best potential outcome.

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Chapter 19
Telehealth System for Effective Treatment in COVID-19 Pandemics

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ABSTRACT

The current coronavirus disease 2019 (COVID-19) pandemic has placed tremendous pressure on the worldwide healthcare systems. The hospitals are instructing patients to quarantine and providing medical facilities to COVID-19 patients at their homes. The feedback and proper monitoring of the quarantined patients is very important for the healthcare system. This situation has forced the use of telehealth systems to offer the delivery of medical facilities over a distance. This chapter presents a wireless telehealth system to monitor the home quarantined COVID-19 patients effectively. When an abnormality is detected then an alert is sent to the concerned hospital or doctor. The presented system allows setting the thresholds and providing alerts, reminders, and notifications to the doctors. The prototype of the presented system has been successfully developed, implemented, and tested, which helps the medical staff to monitor and treat the patients remotely, especially the coronavirus patients who are home quarantined.

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1: INTRODUCTION

Coronavirus disease 2019 (COVID-19) is an acute infectious respiratory disease caused by a newly discovered coronavirus (SARS-CoV-2). The COVID-19 disease affects a respiratory system starting with the ordinary cold and it develops into serious infection like pneumonia as (WHO 2020). The spread of this virus is mainly by droplets of an infected person (Hong, Hao 2020). The governments of various countries are trying their level best to reduce the spread of this virus by using strict lockdown, social distancing, use of masks and personal protective equipments. The lockdown restricts the common people to move around but the necessary medical facilities must be continued to control the spread of the coronavirus epidemic.

All the countries are working on finding a convenient and commercial solution to face the problem of demand and supply of medical facilities to COVID-19 affected patients. The current situation in most countries during this pandemics is a lack of beds in the hospitals. The hospitals are full of COVID19 patients and no more patients can be admitted. Nowadays hospitals are instructing patients to stay at home for the treatment. The patients who have mild to moderate symptoms are therefore sent back to home with proper instructions from medical staff like home quarantine, isolation and medicines. This leads to providing medical facilities to COVID-19 patients at their home. It also frees up the scare resources at the Hospital like ICU beds and ventilators.

This emergency has presented healthcare delivery systems exceptional challenges to monitor and get feedback from such home quarantined patients. This situation has forced the medical system to implement telehealth and altered healthcare delivery at an overwhelming speed (Augenstein J 2020). The telehealth system allows treatments and monitoring without direct or physical contact with the coronavirus affected people (Galewitz P). This ensures the physical social distancing as the affected people are not required to visit hospitals. This helps in reducing spread of the coronavirus (Hollander 2020). Telehealth therefore provides the supply of medical facilities across geographical boundaries. This also reduces the cost and need of personal protective equipment required for medical staff, and gives isolated patients connection with medical staff, and their families and friends (Keesara 2020).

The implementation of suitable telehealth for the current COVID 19 pandemics is a big challenge for the researchers. The telehealth system must be implemented with minimal requirement of the resources and equipment. The implemented system should be cost effective, easy to use by both the patient and medical staff. The telehealth system for the current situation must need to utilise the well adequate and organised facilities offered from the available methodologies. The immediate implementation of the telehealth system for Covid 19 pandemic suggests the use of Internet of Things (IoT) technology (Javaid 2020).

The IoT technology uses the interconnected network for the useful communication of data. The typical IoT system consists of sensors which sense the parameters and send the sensed information through some communication technology to the server or processing unit. The processing unit performs the analysis on the received information and replies back the processed data in the required format to the concerned process. There are many applications implemented data in the required format to the concerned process. There are many applications implemented using IoT in many domains including healthcare too. The use of IoT in healthcare or medicine is referred to as Internet of Medicine Things (ToMT) or Internet of Healthcare Things (IoHT) (Allam 2020).

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The use of such an IoT system to implement telehealth for this Covid 19 pandemic shows an immediate effective and commercial solution. This system will monitor and track the coronavirus related parameters from the patients using IoT. This will ensure the proper follow-up, monitoring and treatment of home quarantined patients. The implementation of such a telehealth system using IoT technology will definitely improve the effectiveness of medical facilities. This will also lead to lessen the workload of the medical staff and treatment cost (Priya S 2019). At the present time, every symptomatic person has to be rapidly recognized and quarantined. It is as well necessary to avoid travel of such patients for the diagnosis, treatments and follow ups. In the current situation of the Covid 19, providing services to the patients using telehealth suggests the best solution.

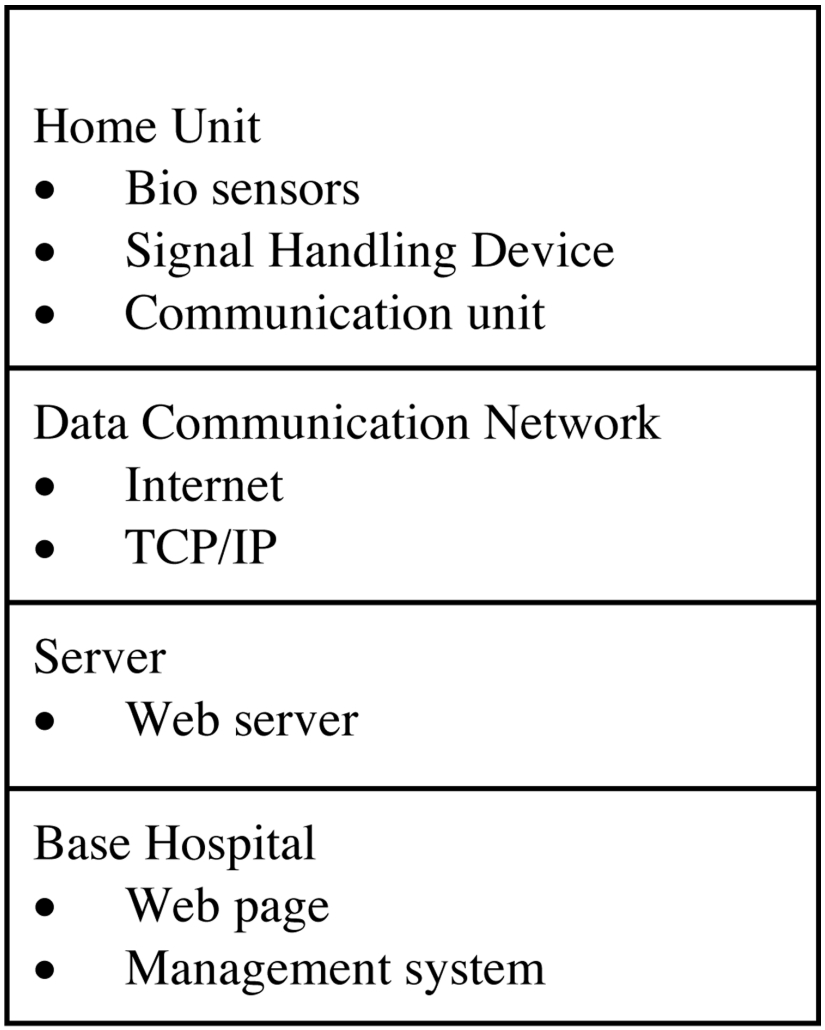
The intention of the telehealth system is to offer healthcare services to the patients located at remote sites using the modern information and communications technologies (Augenstein J 2020). The typical telehealth system is as shown in Figure 1. It consists of biosignal sensors, signal handlining device, data communication networks, hospital site server and management system. The sensor attached to the patient body acquires the physiological parameters and sends them to the signal handling device (A. Hande 2006). The signal handling device collects the bio signals, processes it and analyzes it. This device prepares the data to be sent to the server. Typically data from the signal handling device is sent over the internet using the TCP/IP communication network to the base hospital server (C.-M. Chen 2011). In such systems, the doctor or expert who is evaluating the data is usually accessing the information through web pages using a PC.

The biosensors attached to the patients must be small in size with comfort to the patient providing easy movements of the patients. All these biosensors must communicate with the signal handling device which requires low power consumption sensors (F. E. H. Tay 2009). There are many wireless personal area networking technologies used for communication of sensors with signal handling devices. The signal handling device may be a PC, a smart phone or any embedded device which has a communication module to communicate over the internet to the remote server (Balagangadhar 2017). Once the data is being sent to the server the base hospital system must have an intelligent data investigation system to identify anomalous signals for searching possible chronic diseases (Wang, C 2020).

The use of telemedicine and eHealth as a practical measure to enhance medical care specially during the Covid – 19 situations are presented by (Okolo, A.J. 2021). Their study illustrates importance of telehealth and how to implement the same in the current pandemics. They also discussed the strategies introduced across the world to encourage the management of Covid-19 situation. Their study suggests telehealth systems should be implemented and adopted in the epidemic as a appropriate, secure, accessible, efficient and environmentally friendly method for providing clinical services. The need for visit of the patient to the hospital and spread of the infection is reduced due to use of telehealth systems during Covid-19 (Perrone 20200). They applied the use of telehealth by many sections of the hospitals to investigate different studies. Their study presents the need of telehealth even after the Covid-19 emergency to restructure casualty visits, reducing cost, reducing health budgets of the ministries. Their study concludes the positive input for speeding up and improvement of telehealth tool for pandemic situations. A systemic review was performed to analyse the present condition of the deployment of telemedicine during the current COVID-19 pandemic (Kichloo A 2020). They evaluated the advantages of maintaining telemedicine management in the future also. It is mentioned that the Issues with management and compensation have precluded its full engagement into the healthcare system. The need to prepare for the fully deployment of telehealth in all the regions by overcoming all the current limitations will be helpful for future outbreak of such pandemic situations as well as to obtain the benefits of this service.

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Figure 1. Typical Telehealth system



The telehealth is an essential tool in supervising services while maintaining patients and health workers protected during COVID-19 outbreak (Monaghesh 2020). This result has the capability to avoid any kind of explicit physical interaction, deliver uninterrupted treatment to the society, and ultimately decrease disease and mortality in COVID-19 outbreak. The utmost significant approaches to decrease the development of the epidemic is to adhere to social distancing. Telemedicine links the accessibility with low cost of health-related knowledge and interaction using the Cyberspace and related tools. The use of telemedicine throughout the coronavirus epidemic has been the doctor's main protection to decelerate the proliferate of the coronavirus (Vidal-Alaball 2020).

Telemedicine systems should be used to prevent overcrowding while preventing human exposures and facilitating high-quality care (Rockwell 2020) . The regulations and guidelines of various nations have progressed to accelerate better compensation for and implementation of numerous telemedicine prototypes. Although some legitimate, governing, and compensation challenges remain, the COVID-19

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epidemic could be the appropriate motivation for policymakers and governing agencies to announce additional methods that enable more extensive implementation of telemedicine systems worldwide.

The National Telemedicine Canter of China (NTCC) has launched the Emergency Telemedicine Consultation System. This is a telemedicine-aided epidemic warning and reaction system to provide health services remotely through terminals across hospitals (Zhai 2020). They believe in the use of telehealth systems perform an important role in delivering disasters and large-size epidemics in high indecision situations. The experiences acquired from this pandemic give perceptions to monitor public health organizations as they execute telehealth to improve strength to upcoming pandemic occurrences.

The telehealth system presented is evaluated for the treatment of patients with enlightened COVID-19 who are home-quarantined (Xu, Hui 2020). The implemented telehealth system monitors several key parameters and symptoms. The observed the reduced risk of delayed hospitalization. The self-assessment tools provided with the system helps them to assessment of their conditions. This helps to medical staff to take proper and suitable medication assessments. The procedure involves a small number of workforces to operate a huge group of patients.

A simplified framework for telemedicine in the COVID-19 pandemic has been defined for the efficient implementation (Ohannessian 2020). All stakeholders are urged to focus on the disputes and work together to encourage the reliable and evidence-based utilization of telehealth throughout the existing epidemic and upcoming epidemics. The existing pandemic situation is a sign to implement the essential governing structures for establishing broad implementation of telehealth systems in their national health care system.

Here we presented a wireless telehealth system for the current Covid 19 pandemics. The proposed system consists of biosensors which are detecting vital body parameters related to coronavirus. The collected biosignals are transferred to the smartphone via Bluetooth for further processing and sendinding to the central server using the internet of the smartphone. The data is analysed in the cloud and further sent to the doctors in various forms. An application is developed in the smartphone so that the patient can also check and monitor the parameters. All the parameters of each patient are sent to the cloud so that continuous monitoring is possible. When an abnormality is detected then an alert is sent to the concerned hospital or doctor. The rest of the chapter is organized in three sections as follows. The presented system which has been implemented and tested is presented in Section 2. Lastly Section 3 includes some discussions and conclusions.

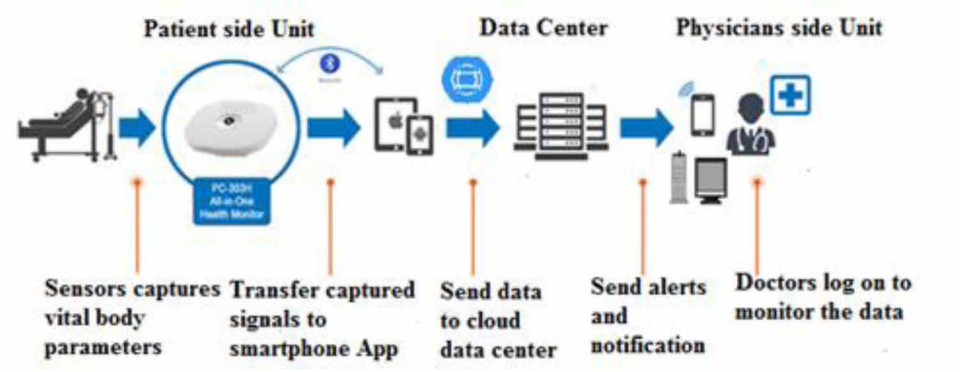
2: SYSTEM DESIGN

This section presents the details of the design and implementation of the preesented telehealth system for Covid 19 Pandemics in detail. The architecture of the proposed system is presented in Figure 2. The proposed telehealth system utilizes the advanced sensor technology, recent communication technologies and the affordability for flawless implementation and ease of use for patients as well as doctors. It will automatically send the alerts to the doctors/hospitals whenever a preset parameter exceeds its threshold.

The presented architecture is designed and implemented for effectively treating the home quarantined patients using physiological sensors and intelligent data analysis for essential parameters related to coronavirus. It primarily consists of the following elements.

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Figure 2. Architecture of the telehealth system for Covid 19 Pandemics



Patient side Unit: It consists of biosensors connected to the patient's body to acquire physiological parameters. These parameters are acquired by a designed device and send all the data to the smartphone via Bluetooth. A special App installed in the Smartphone will collect the data from the biosensors. This App has an intelligent data analysis system to display the parameters and send the data to the server using the internet. Special features are added in the App which are described in further description to ease the user for operating and adding many patients in the same App.

The Data Center: The data from the smartphone App is pushed to the central server for the analysis. We have used the cloud to store and analyze the data received from each patients smartphone App. Doctors log on to this cloud server to looks at patient's data and suggest suitable course of treatment. While the data is currently being stored on service provider's cloud server, the architecture is open enough to push the data to in-house system of any Hospital.

Physicians side Unit: This side gives an access to the medical staff to the analyzed data from the data center. We have implemented two modes for the same. In the first mode doctors have a smartphone based access through installed App or by using through web based access mode. The medical staff examines the vital signs related to coronavirus and decides the actions and feedback to the patient. The data center also sends an alarm to the doctor/ hospital in any abnormality in the received data from the patient.

2.1 System Components.

This sub section describes the system components of the presented telehealth system for coronavirus patient monitoring and treatment.

1.**Patient monitoring device**: The presented telehealth system implements the health monitor which is portable, lightweight and easy to use for the patient. It mainly consists of vital-sign signal acquisition and communication module. Thus it collects important bio signals related to coronavirus disease. The critical parameters need to check for any Covid 19 patients are body temperature and blood oxygen levels (Guan, W. J 2019). The patients who have medical history like blood sugar or blood pressure comorbidity then other parameters need to be monitored to reduce mortality rate. For such cases parameters like ECG, blood pressure, blood glucose level needs to be critically monitored during treatment of coronavirus (Ghosh A 2020). We have designed a compact single

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health monitor which acquires six vital coronavirus related signs namely body temperature, blood oxygen level, heart rate, ECG, Blood glucose and blood pressure.

Body Temperature Sensor. The temperature of a healthy person is around 37 °C. It is of great medical importance to measure body temperature during the Covid-19 pandemics. This is the basic and very first sign affecting a coronavirus. The measurement of body temperature helps in the efficient treatment and monitoring of the coronavirus patients by the physicians. The sensor is designed based on infrared sensing technology. The measuring range of the body temperature utilized in the proposed system is 28 – 42 degree Centigrade. The measuring error: $\pm 0.2\%$ for 35 – 42 degree Centigrade and $\pm 0.4\%$ for $<$ 35 degree Centigrade.

Blood Oxygenation saturation sensor: Blood oxygenation saturation is also termed as SpO_2 measurement. It determines the saturation of oxygen in the blood. This parameter also is of prime importance for the corona patients to be monitored (Behar 2020). The corona patient normally has very low value of SpO_2. It consists of a reusable finger clip sensor that uses contoured silicone pads. This pad makes contact with the patient's finger. The optical elements pass the light through transparent silicone windows into the patient's finger, resulting in a percentage of blood oxygen saturation.

ECG sensor - The heart's electrical activity is recorded using an electrocardiogram recorder. It is plotted as amplitude of electrical activity of heart versus time (S. Kho´or 2003). The ECG recorder is designed using single lead input impedance of greater than 10MegaOhm. The Sensitivity tolerance is less than 10% and 50 Hz interference suppression filter is greater than 20 dB. The recorder has a frequency response of 0.5 to 40 Hz.

Blood pressure and heart rate sensor: To measure the blood pressure a cuff having 25 to 35 cm perimeter is provided. It records the systolic, diastolic, mean pressure and heart rate using an oscillometric method in a single measurement. The blood pressure measuring range for this sensor is 0 to 300 mmHg. The range for heart rate is 40 to 180 BPM. The recording of these parameters takes approximately 40 to 140 seconds.

Blood Glucose: The level of glucose in the blood is measured by applying a drop of blood to a chemically treated, disposable test-strip, which is then inserted into an electronic blood glucose meter. The reaction between the test strip and the blood glucose is detected by the meter and displayed in units of mmol/L. The sensor mainly comprises low-pain lancets, lancing devices and test strips.

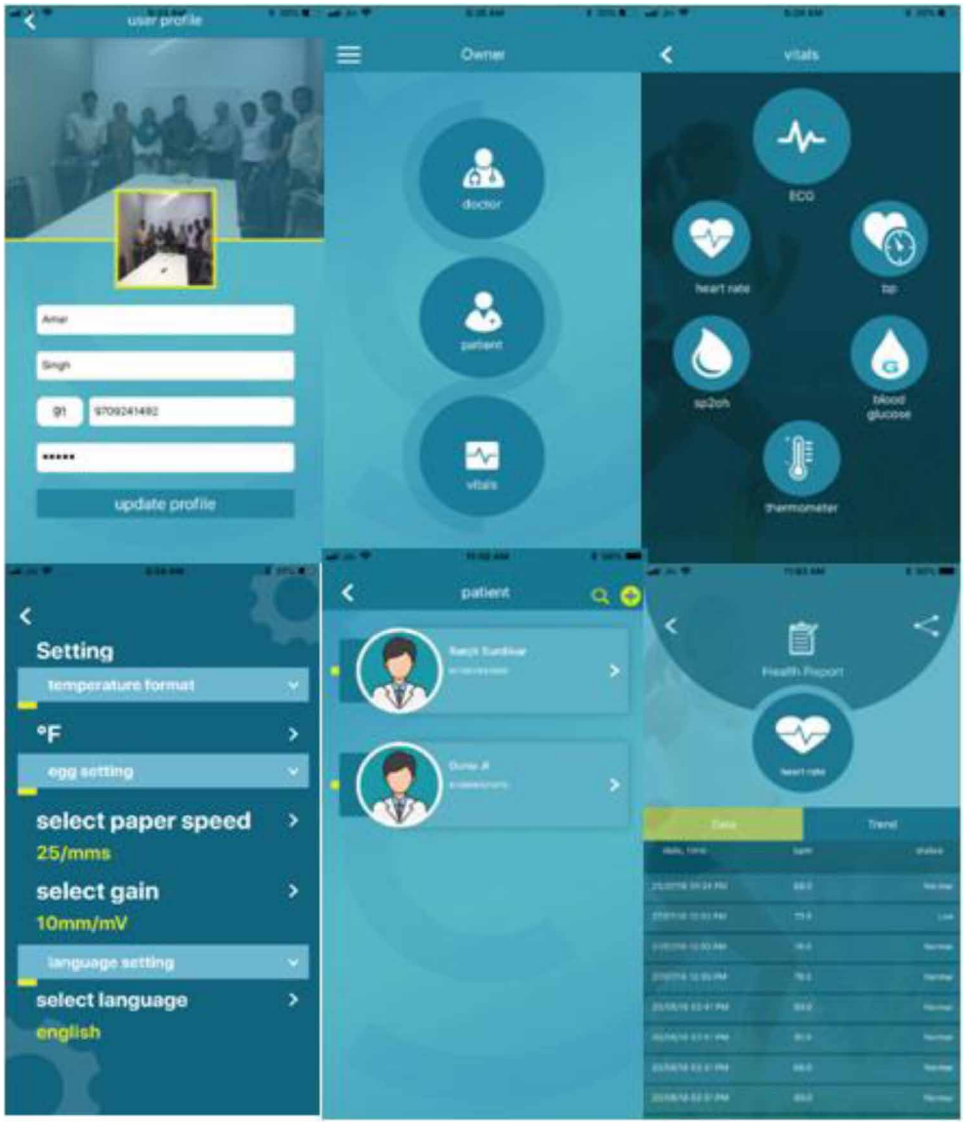
The patient monitoring device captures six parameters which are prime important for a coronavirus patient. The device is compact and easy to use using sensors, probes and other related accessories.

2. **Smartphone with mobile application:** The dedicated mobile application is developed for processing of the acquired bio signals in the smartphone. The developed application synchronizes, controls, and preserves the correct procedure for monitoring, displaying and communication of these bio signals. The App is developed for android and iOS mobile operating systems. The developed App is simple to use and user friendly which does not require any training. To record a specific bio signal the patient has to simply select the parameter to record from the app user interface and the data gets recorded in the mobile flash memory. Like this all six parameters and as per the suggestions of the doctors, patient has to just record the biosignals using sensors and mobile app. The mobile app immediately displays the recorded value on the screen and also the same is sent to the cloud data center for further storage and processing. The mobile app is designed to add up to five patients in a single mobile app. There may be the case that in a single home more than one coronavirus patients

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are home quarantined. So using a single patient monitoring device and the same mobile app up to five patients data can be accessed, monitored, stored and sent to the data center. This saves the cost for the patients. The screen shots of the user interface of the app is as shown in Figure 3.

Figure 3.The user interface screenshots of the developed mobile app.



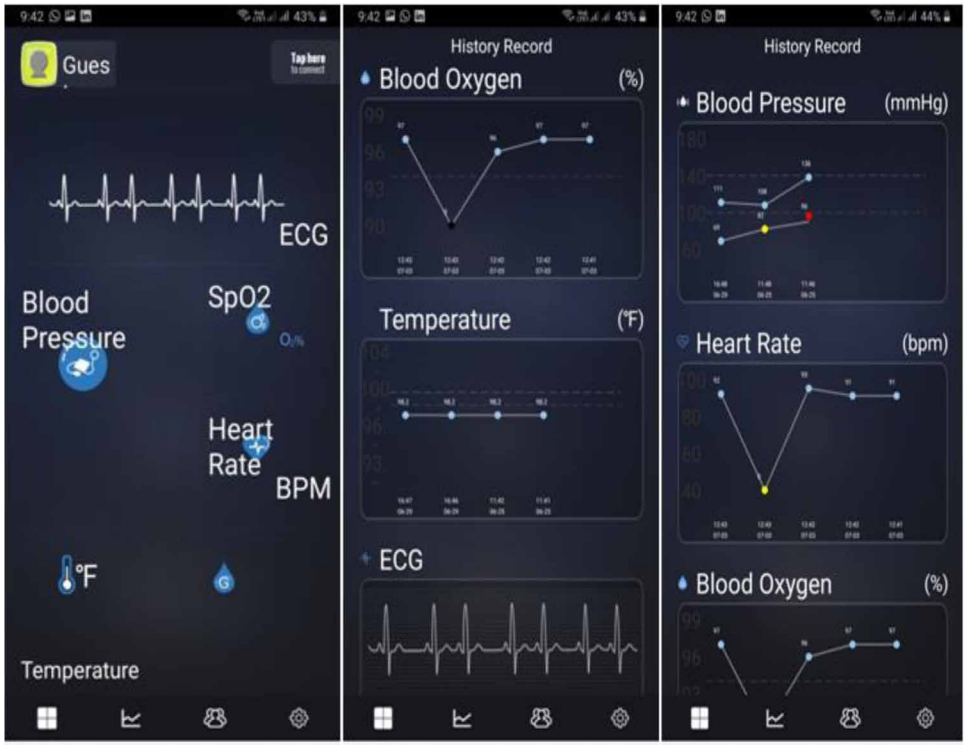
3. **Data Center:** The remote data center has been utilized for receiving, storing, processing and analyzing the vital sign data received from patients. The data center gives access to the medical staff to monitor, archival and analyze the patient's records and progress during the treatment. The authorized user gets access to the received patient's data through either mobile application mode or web based access mode. The cloud server would be typically high performance server with

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multiple disks to guard against disk failures (Wang 2017, Gong 2020). The Hardware runs Linux Operating system with MySQL Database. The data sent by smartphone is stored in this database on the server. The data so collected in the cloud is analyzed and alerts are generated on sensing any anamoly. Here the received data is displayed to the medical personnel in their office anywhere in the world. The alerts as explained above are also provided to the doctors so that doctors do not have to examine heaps of data pumped to the cloud server, but concentrate only on exceptions.

4. **Physicians side Unit:** We have designed with two options for accessing and managing the patients by the medical personnels. The mobile application program is developed for Android and iOS mobile operating systems for accessing the data center. This helps doctors to get access to the data center from anywhere and anytime. The enterprise version is developed for the hospital where an access to the data center is through the web pages. The web based access method allows many users such as doctors and other relevant medical staff to connect the data center using a standard web interface through the internet. Both the versions have several unique features which are incorporated in the proposed telehealth system for Covid 19. In both modes doctors can add new patients, new consultation, and instructions. The six biosignals recorded from the patient side unit are displayed and respective thresholds can be set for the alerts. The data is stored and the trend views are also presented to the doctor through App or web page. The screen shots of the designed App tomonitor the recorded data and trends are shown in Figure 4.

Figure 4. Screen shots of the designed App to monitor the recorded data and trends



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The proposed system is implemented for assessment of the key parameters of the home quaranince patients specially in India, Maharashtra state regions. The impelemneted system helps medical staff for correctly monitoring and delivery of the correct guidalines to the Covid-19 affected home quarantined patients.

3. CONCLUSION

As the number of coronavirus patients is increasing day by day in this current Covid 19 pandemic, almost all the health care systems worldwide are suffering with effective treatment. This leads to development of new, unique and innovative approaches to manage the current situation. The uses of telehealth have a critical role in Covid 19 pandemics. It helps in rapidly deploying the medical facilities to a greater extent. This helps to reduce the burden on front line medical service providers. It allows providing the services whenever hospitals are full of coronavirus patients or when they are unable to meet the demand of the treatment. This ultimately decreases the risk of transmissible coronavirus due to remote treatment by the use of proposed telehealth system. The development, implementation, and awareness of such telehealth systems are the need of the hour so that such systems become conventional components of the healthcare sector.

This chapter presented the design and implementation of a telehealth system for effective treatment in this Covid 19 pandemic situation. The vital signs of the patients are captured and transmitted to the data center in the cloud using smartphone over the internet. The dedicated application captures bio signals and transmits these signals to the cloud. The intelligent algorithms in the data center analyze these signals, stores and gives access to the medical staff for further monitoring and treatment. The access to the medical staff to the data center is provided either through smartphone based application or web based interface. Both the modes of accessing the data from the cloud are user friendly for treatment and monitoring the patient remotely.

The proposed system implements a patient device to acquire essential six physiological parameters related to coronavirus. The patient device transfers all the captured data to the smartphone through Bluetooth using a developed mobile application. The application transmits all the data to the cloud data center where it is processed and stored. The doctors and medical staff can choose to access the data center either by using the same smartphone application or web based interface. Once medical staff get access to the data, they can set the thresholds to the parameters. The alarms are automatically generated and sent to the doctors through SMS to alert the emergency. The data center stores the history of the captured parameters as well as the trends are displayed for the parameters. The key features of the system to set thresholds, to provide alerts, reminders, and notifications helps the medical staff to monitor and treat the patients remotely, especially the coronavirus patients who are home quarantined.

DECLARATION OF CONFLICTING INTERESTS

The Authors declares that there is no conflict of interest.

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Chapter 20
Telemedicine-Based Diabetic Care Powered With Artificial Intelligence

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ABSTRACT

Diabetes is one of the chronic diseases which keep increasing at an alarming rate, and the patients need to visit the clinic to routinely check their sugar levels and adjust their treatment plans. Artificial intelligence-enabled telemedicine is found to be a promising approach to monitor the health status of diabetic patients. Some of the promising artificial intelligence technologies for treating diabetic patients are a reactive machine, limited memory, theory of minds, and self-awareness. Each of these techniques is discussed with architecture, characteristics, algorithms, advantages, and applications. Performance analysis is carried out towards the performance metrics like accuracy, medical error rate, speed, and learning rate, and the performance achieved by self-awareness artificial intelligence technique is found to be better in delivering telemedicine-based care for diabetic patients with a very high level of precision and speed of operation.

INTRODUCTION

The diabetic is one of the chronic diseases which keep increasing at an alarming rate and according to World Health Organization (WHO) around 463 million populations is suffering from diabetes and may reach 700 million populations by 2045. The diabetic disease process begins with the deficiency of the insulin in the patient body followed by hyperglycaemia, polyuria, ketoacidosis, breakdown of the nutrients, and polydipsia after that the actual clinical symptoms of diabetes are exhibited. A high-level view of the diabetes process is shown in Figure 1. Diabetic patients need to visit the clinic to routinely check up their sugar levels and adjust the treatment plans along with the lifestyle changes as per the advice of the doctor. The commonly used mode of treatment in telemedicine is chat platform or Audio/Video

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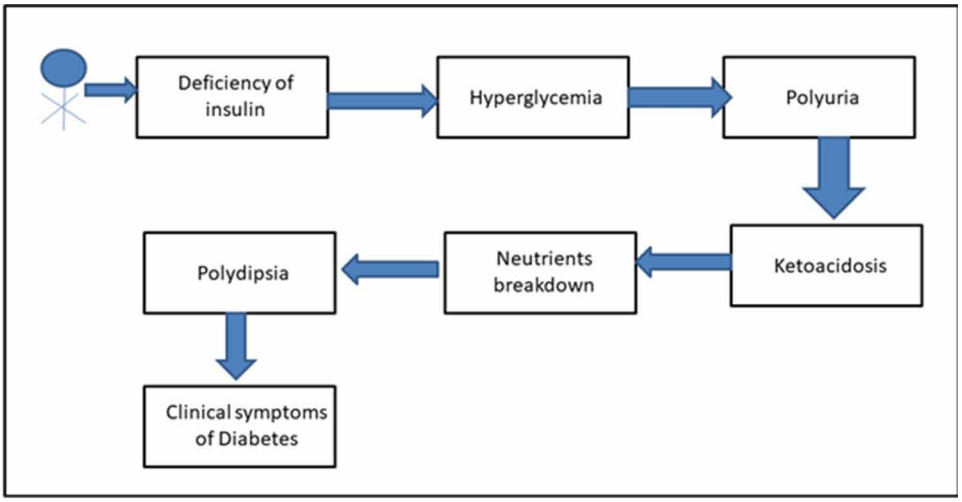
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platforms involving the telemedicine consultations like patient-doctor, care giver-doctor, doctor-doctor, and health care worker-doctor [1, 2].

The Artificial Intelligence Technique (AIT) works in six stages i.e., perceiving the information in the environment, processing the perceived information, enabling learning of the machines, planning the actions, and performing the suitable actions (Nir et al., 2019; Raj, 2019). The decisions taken through AIT is accurate as it involves self-learning, reasoning based on the learning, and self-corrections based on the errors detected. Now we can find a vast application of AIT in various fields like education, healthcare, tourism, banking sector, business, automobile industry, social media, and many more. On a higher level the AITs are classified into two types i.e., weak AIT and string AIT. Weak AIT is also referred to as narrow AIT in which the algorithm is trained to do only a specific type of task. Two of the popular voice controller assistants fall under the category of weak AIT i.e., Siri and Alexa as both of them perform categorization tasks and have predefined responses. Strong AIT is also referred to as general artificial intelligence which is incorporated with human cognitive capabilities to operate beyond the pre-programmed logic and perform the tasks which are not familiar. Some of the popular strong AITs include language translation, recognition of speech, automated artificial decision-making systems, and many more (Azizi, 2019).

Figure 1. A high-level view of the diabetes process



The increasing capability of the AIT has raised its application in almost all forms of healthcare like primary care, emergency care, long-term care, remote, telemedicine, store, and forward monitoring, and so on, which offers a new model of health care services to the patients. Among all forms of monitoring, the application of AIT in the field of telemedicine for treating diabetic patients has improved the quality of treatment and has increased the life expectancy of the patients (Ananthakrishnan & Singh, 2020). The differences between conventional telemedicine and AIT-enabled telemedicine towards performance metrics are shown in Table 1.

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Table 1. Conventional telemedicine versus AIT enabled telemedicine

Performance metrics	Conventional telemedicine	AIT enabled telemedicine
Patient satisfaction	Medium	High
Medication adherence	High	High
Health complications	Medium	Low
Medical errors	High	Low
Access to care	High	High
Diagnosis accuracy	Medium	High

The AIT-enabled telemedicine for diabetic care has performed a revolution in the field of diabetic care especially during the time of the covid pandemic. The continuous remote monitoring of diabetic patients provides precise treatment for diabetic patients by controlling the level of glycemia, glucose, and hemoglobin. Four forms of AIT which are categorized based on their functionality performed are widely used to perform telemedicine-based diabetic care which includes reactive machines, limited memory, theory-of-mind and self-awareness. Reactive machines are reactive and do not store past experiences, limited memory works by looking at past experiences, a theory of mind works by understanding the objects of the real world through a thought process, and self-awareness builds representation by themselves and work. Some of the advantages offered by artificial intelligence oriented telemedicine in treating the diabetic disease are a highly intelligent level of diagnosis, effective collaboration among the health care professionals, cost-effective mechanism, minimizing the dosage errors, sufficient clinical trial participation, early prediction of side effects, performing diabetic retinopathy precisely, automated extraction of cardiac rate from ECG signals, providing guidance for injecting insulin, suggesting lifestyle modification, insisting exercise to control the blood sugar level, prediction of the blood glucose level in near future, preventing long term complications, estimating the chances of heart attacks, Chabot for interaction with the patients, providing real-time feedback to the doctor, and many more (Parikh et al., 2020; Pradeepa et al., 2019).

BACKGROUND

The works carried out in literature towards diabetic care through telemedicine are discussed below along with their limitations.

Telemedicine is considered to be one of the promising approaches for treating chronic diseases, especially diabetes as it bridges the gap between the patient and clinic which is discussed in (Malasanos & Ramnitz, 2013). Diabetes in adults and even in children having type 1 diabetes and type 2 diabetes are being diagnosed using telemedicine and many programs are launched for synchronous and asynchronous telemedicine. It has been reported that the efficiency achieved through asynchronous intervention is better compared to the synchronous interventions and in many cases combines the approach of synchronous and asynchronous are being followed.

The use of telemedicine for treating diabetes patients during covid 19 pandemic time and lockdown tenure during which the chances of getting affected with the coronavirus is more is discussed in (Ghosh et al., 2020). To communicate with the healthcare professionals, several modes of communications are

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used which include text, audio, video, Emails, and so on. However in a country like India telemedicine is subjected to various legal issues towards practicing, transfer of private data, clinical assessment, and running of courses.

The use of artificial intelligence for diabetes care is considered as one of the improvements in the field of the health care domain (Samer, n.d.). The machine learning algorithms are designed to predict the chances of getting diabetic early from the symptoms and a decision support system is developed using which both patients and doctors are mutually benefitted. The developed algorithms tell the necessity of the paradigm shift from conventional telemedicine to artificial intelligence enabled telemedicine to provide precision care.

The artificial neural network is incorporated made used for developing telemedicine based solutions for chronic patients in (Gheorghe, 2015). Since the chronic dataset is available publicly for free of cost they are made use for training the neural network which gives exact prediction about probability of occurrence of the disease. The neural network developed act as an assistance for physician or doctor in taking clinical decisions at the time of uncertainty. The main job of the neural network is to identify the hidden patterns in the field of telemedicine domain and assist doctors in taking the medical decisions.

The recent trends in telemedicine using artificial intelligence are mentioned in (Pacis et al., 2018). The flexibility and versatility feature exhibited by the artificial intelligence algorithms give endless opportunities to the scientists to develop solutions rich in artificial intelligence to medical problems. Their are several implementation challenges in the process being followed which include following improper cost model, instable delivery of medical services, poor infrastructure, more consumption of bandwidth and many more. Due to the availability of high performance technologies the implementation issues of artificial intelligence is being reduced and is used in each step of medical science which include monitoring of the patients, extracting the healthcare information, medical diagnosis through intelligence and even analysis of complex medical issues.

The use of deep neural network is found to be useful in diagnosis of diabetic retinopathy as discussed in (Ramachandran et al., 2018). The deep neural network is capable of learning patterns of large dataset to determine mild and severe medical conditions. The conventional neural network algorithms were found to be more sensitive towards to the effect of outliers and the accuracy rate dropped poor diagnosis and identification of patterns. However this limitation is overcome using deep neural network algorithms which are now integrated with community screening to accurately interpret the patterns in tomography scanned images of diabetic patients. This serves as valuable asset in identification of complex tumours and provides nationwide service to the diabetic patients.

Convoluted neural network is used to do automated diabetic retinopathy in (Zeng et al., 2019) which is found to be promising solution to predict the probability of blindness for diabetic patients. Using technique it is really difficult to determine the diabetic retinopathy and is time consuming also which is successfully managed by the convoluted neural network by properly classifying the retinal images into harmful and non-harmful cases. Study shows that by using ensemble of several convoluted neural network, the accuracy achieved in detecting the diabetic retinopathy is higher as it significantly identifies the correlation between the input images and the prediction model used.

To summarize the existing works, most of the works use a conventional telemedicine approach for treating diabetic patients. The approach was found to be good as it reduced the death rate and the number of hospitalizations. However, the frequent visit for clinical checkups must not be ignored, the chances of dosage errors and side effects are more. Many papers have highlighted the impact of artificial intel-

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ligence technologies on telemedicine but complete automated AIT-enabled telemedicine frameworks and complete design of operation are not developed for treating chronic patients especially diabetic patients.

MAIN FOCUS OF THE CHAPTER

The main focus of the chapter is to introduce artificial intelligence-based telemedicine approaches for treating diabetes. It begins with the comparison of conventional telemedicine and artificial intelligence then some of the potential artificial intelligence approaches like a reactive machine, limited memory, a theory of mind, and self-awareness are discussed in treating diabetic patients with supporting architecture and algorithms.

SOLUTIONS AND RECOMENDATIONS

The applications of potential artificial intelligence techniques which include reactive machines, limited memory, theory of mind, self-awareness in treating diabetes patients along with their design and algorithms is discussed in this section followed by performance analysis towards various performance metrics.

REACTIVE MACHINES

Reactive machines are one of the basic forms of AIT that operate by not storing any past data in the memory and takes the decisions based on the current actions (Debnath & Bardhan, 2020). In this technique, the algorithm perceives the environment as it can see and does not consider the previous knowledge gained about the internal world of operation. The memory about all forms of past moments will be discarded, and the main focus will be only towards the present moment. A high-level view of the reactive machines-enabled telemedicine system for diabetic care is shown in Figure 2.

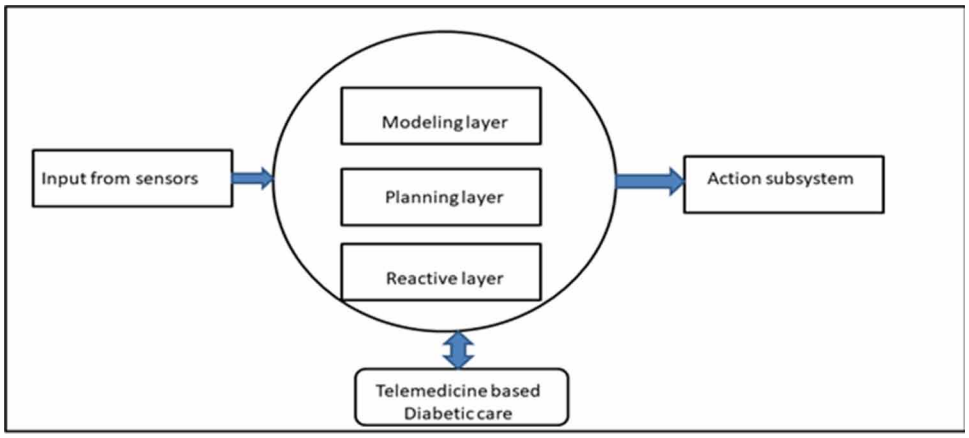
It works by gathering the data from the sensor devices which is fed as input to the reactive machine which is composed of three layers i.e. modelling layer, planning layer, and reactive layer. Based on the input images fed the reactive machine first does the modelling of the images then performs the planning over the modelling performed and then reactive actions are taken. The actions taken by the reactive system are gathered together to form the action subsystem which provides diabetic treatment decisions. The working of the reactive machine-enabled telemedicine system for diabetic care is given in algorithm 1.

Algorithm 1: Algorithm for reactive machine enabled telemedicine system for diabetic care
1: **Begin**
2: **INPUT:** ***Sensor Input*** $SI = \{si_1, si_2, si_3, \ldots, si_m\}$
3: **OUTPUT:** ***Action Subsystem*** $AS = \{as_1, as_2, as_3, \ldots, as_m\}$
4: **# Modeling layer**
5: **For** each sensor input st_i in SI **do**
6: Compute model output $MO = w_0 st_0 + w_1 st_1 + \ldots + w_n st_n$, where $w_0, w_1, \ldots, w_n$ are the weights assigned for the sensor input.
7: **End for**

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8: **#Planning layer**
9: **For** each model output mo_i in MO **do**
10: Compute planning output $PO = w_0F(mo_0) + w_1F(mo_1) + \ldots + w_nF(mo_n)$, where $F(mo_n)$ is the fitness value of each of the model output.
11:**End for**
12: **# Reactive layer**
13: For each planning output po_i in PO **do**
14: Compute maximum likelihood variance $MLV(po_i) = argmin_{\theta \in \oplus} po\left(\oplus; po_i\right)$, where
15: Calculate action subsystem= $1/MLV(po_i) \sum \tau\left(\oplus; po_i\right)$
16: **End for**
17: **Output** Action Subsystem $AS = \{as_1, as_2, as_3, \ldots, as_m\}$
18: **End**

Figure 2. A high-level view of the reactive machine enabled telemedicine system



Reactive machines perform the actions suggested by the host as they do not contain any brain of their own. Deep reactive machines are being used nowadays to precisely respond to different types of stimuli. Reactive machines include several advantages which include faster decision-making capability, cost-effectiveness, minimum time consumption, robustness, fault-tolerant, self-awareness, determine future actions precisely, repair restoration, ease of monitoring, maintenance optimization, and so on. However reactive machines have few disadvantages which include several safety issues that occur re-concurringly, energy consumption is more, poor usage of experience, lack of proactiveness, instability is high, a risk factor is more, adaptation is limited due to hardwired usage, vulnerable to unseen input scenarios, and so on.

Some of the applications where reactive machines are used include determining the opponent move in the chess, online helpdesk, customer relationship management, student-teacher alert system, directing the direction of the car, artificial visual assistance system, assisting the travellers in buying the ticket, developing machines with verbal understanding, development of automated vehicles, speech identification,

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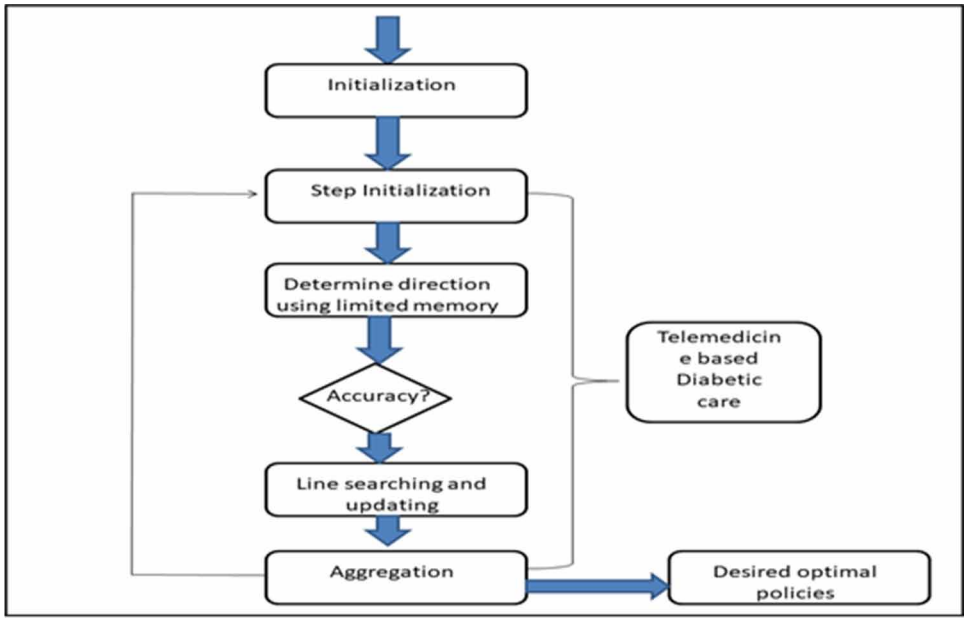
machine vision, classification from text to speech, personalized drug development, tailored radiotherapy, travel price determination, and so on (Gambus & Jaramillo, 2019).

Limited Memory

Limited memory is the second form of AIT which stores the results of the previous events and uses the knowledge obtained from the previous events to solve the new upcoming problems. The previous data are getting stored only for a short period hence the name as limited memory. The limited memory operation begins with the initialization followed by step initialization and the process of finding direction search using limited memory is repeated until the desired level of accuracy is obtained. The searching operation performed is limited, and updating happens through line searching and updating simultaneously. After completion of the initialization process, an aggregation operation is performed to generate desired optimal policies (Badem et al., 2018).

A high-level view of the limited memory-enabled telemedicine system for diabetic care is shown in Figure 3. The working of limited memory enabled telemedicine system for diabetic care is given in algorithm 2. Some of the advantages of limited memory which makes it suitable for continuous monitoring of diabetic patients are takes accurate decisions in hostile conditions, increased level of automation, customization of repetitive tasks, ease strategizing of complex tasks, performing high computational tasks at less speed, developing an artificial scoring system, classification of multimedia documents, storing history for a longer time, accurate critical decision-making ability, high level of cognition ability, solving complex problems in nonpolynomial time, high level of tolerance towards imprecise data, nonlinear manner of processing for accurate results, high speed of operation through parallel execution, mining patterns from experimental data, clustering of high-resolution images, flexibility in the state of operation, provides a deterministic solution to versatile problems, and so on.

Figure 3. A high-level view of the limited memory enabled telemedicine system



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Some of the popular applications of limited memory include automated self-driving vehicles, fitting algorithms for low dimensional datasets, solar energy harvesting, data indexing, textual information retrieval system, tailored edge devices development, voice assistant applications, medical applications development at low cost, persistent block accessed media, deploying optimal algorithms in edge devices, food delivery, drug administration system, development of decision support system, analysis of large scale power systems, performing case-based reasoning for medical problems, developing mathematical models for interactive systems, probabilistic computing for handwriting recognition, and so on (Murshed et al., 2019).

Algorithm 2: Algorithm for limited memory enabled telemedicine system for diabetic care
1: **Begin**
2: **INPUT: Limited Memory Input** $LMI = \{lmi_1, lmi_2, lmi_3, \ldots, lmi_m\}$
3: **OUTPUT: Desired Optimal Policies** $DOP = \{dop_1, dop_2, dop_3, \ldots, dop_m\}$
4: **# Initialization**
5: **For** each limited memory input lmi_i in *LMI* **do**
6: Perform step initialization $LMI = \{lmi_1 = \varnothing,\ lmi_2 = \varnothing,\ lmi_3 = \varnothing, \ldots.\ lmi_m = \varnothing\}$
7: Determine the direction using limited memory $\mathrm{dir} = \frac{\mathrm{a}}{\sqrt{\mathrm{a}^2 + \mathrm{b}^2 + \mathrm{c}^2}}$, where a, b, and c Are direction ratios
8: **If** desired accuracy is reached
9: Perform line search $ls_i = y - y_1 = m(x - x_1)$, where m is the slope, x, y, x_1 and y_1 are dependent and independent variables
10: Aggregate the output generated by the line search
$dop_1 = \{ls_1 \cup ls_2 \cup \ldots \cup s_m\},\ dop_2 = \{ls_1 \cup ls_2 \cup \ldots \cup ls_m\},\ dop_m = \{ls_1 \cup ls_2 \cup \ldots \cup ls_m\}$
11: **End If**
12: **End for**
13: **Output** Desired optimal policies $DOP = \{dop_1, dop_2, dop_3, \ldots, dop_m\}$
18: **End**

Theory of Minds

Theory of minds is the third form of AIT which tries to mimic individual human degree of capacity to understand others. AIT can represent the human mental state representation. The mental states are considered for representation beliefs, emotions, desire, intents and knowledge, and so on (Debnath & Bardhan, 2020). One of the necessities of a theory of mind establishes the fundamentals of social interaction by having the capability to predict the behavior of others. For humans, children learn the skills early in childhood by observing people or even trying to copy them. The same strategy of humans is used in machines to assess the observable states of others by understanding the consequence of emotions and even trying to understanding the likes and dislikes of people. For humans, children learn the skills early in childhood by observing people or even trying to copy them. The machine starts to learn by formulating the policies through interaction with the emotions and thoughts of humans. Currently, machine learning algorithms perform the tasks as directed by humans that are one-way relationships. Two popular examples are Alexa, Google maps, and Siri which just follow the instruction and lacks emotional

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support. The process of working of a theory of mind works in six layers i.e. in the first layer identifying the agents, establishing the goals, and assessing the intentionality of the learning. In the second layer, limitation of learning is highlighted with mimicry and empathy. The third layer does joint attention and visual perspective communication. The fourth layer performs the projection and simulation. At last in the fifth layer, the mental state inference will be drawn over the environmental state of representation. A high-level representation of the theory of minds enabled telemedicine system for diabetic care is given in Figure 4 and detail of working is given in algorithm 3.

Advantages of a theory of minds are many some of them are listed as follows retrieval of large scale data, gathering of data from multiple sources, updating policy evidence, linear regression, testing of hypothesis, reproduction in a commercial scenario, hashing of unique keys, reproduction of isotopic spectrum, flexible online communication, virtual personal assistant, automated cars development, generation of product recommendations, Google translation engine, categorization of photos, statistical analysis of financial data, human-computer interaction, production of new stable materials, colouring of black and white images or movies, content personalization, generating sound alerts, commute predictions, revision of search engine results, filtering of malware, data crowdsourcing, outbreak prediction, and many more.

Applications of theory of minds are as follows tracking of dales belief propagation, managing social situation which require the mental state of knowledge, managing the orientation of human heads, pervasive care through cognitive reasoning, performing reflective reasoning operations, autism training, developing customized web experiences, recognizing the human emotions, passing pre-trial instructions to beginners, understanding the human relationships, handling the self estimation issues, classroom learning, peer intervention methodology, testing the school-aged students learning ability, employment of pedagogy methodology, conducting schooling activities in social context, playing proprietary music, tracking eyes of the children's in school and colleges to monitor their attention, probabilistic reasoning in healthcare, cleaning of data from multiple data sources, performing exploratory data analysis, medical diagnosis of tumours, analysis of big datasets, understanding of natural languages, performing meta-learning operations, performing core digital transformation views, detecting low speed processing operations in power systems, and so on (Shum et al., 2019).

Algorithm 3: Algorithm for theory of minds enabled telemedicine system for diabetic care

1: **Begin**

2: **INPUT: Limited Memory Input** agents $A = \{a_1, a_2, a_3, \ldots, a_m\}$, goals $G = \{g_1, g_2, g_3, \ldots, g_n\}$, and intentions $IN = \{in_1, in_2, in_3, \ldots, in_o\}$

3: **OUTPUT: Mental states** $MS = \{ms_1, ms_2, ms_3, \ldots, ms_p\}$

4: **# Initialization**

5: **For** each agent a_i in A **do**

6: Perform agent initialization $A = \{a_1 = \varnothing,\ a_2 = \varnothing,\ a_3 = \varnothing, \ldots .\ a_m = \varnothing\}$, goal initialization $G = \{g_1 = \varnothing,\ g_2 = \varnothing,\ g_3 = \varnothing, \ldots .\ g_n = \varnothing\}$, and intention initialization $IN = \{in_1 = \varnothing,\ in_2 = \varnothing,\ in_3 = \varnothing, \ldots .\ in_0 = \varnothing\}$

7: Compute Empathy $Emp = \sqrt{\dfrac{P(1-P)}{m}}$, where P is the weight average of actions, goals, and intentions

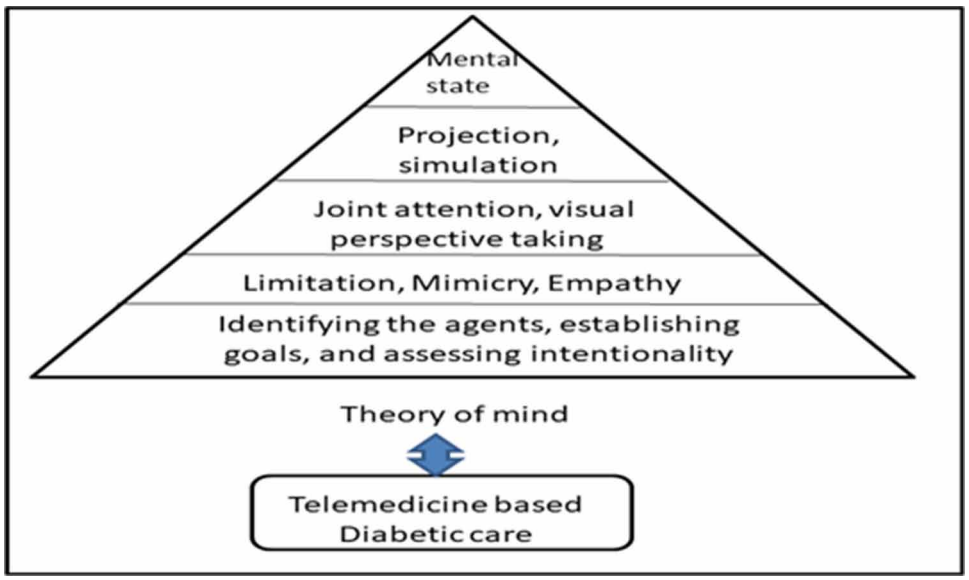
8: Determine joint attention i.e. $\mathrm{JA} = \dfrac{\mathrm{Emp}}{\sqrt{\mathrm{A}^2 + \mathrm{G}^2 + \mathrm{IN}^2}}$, where a, b, and c are direction ratios

9: Perform projection $P = Emp(a_m - a_1) + Emp(g_n - a_1) + Emp(in_o - a_1)$

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10: Aggregate the projections computed to compute the mental state
$ms_1 = \{ms_1 \cup ms_2 \cup \ldots \cup ms_m\},\ ms_2 = \{ms_1 \cup ms_2 \cup \ldots \cup ms_m\},\ ms_m = \{ms_1 \cup ms_2 \cup \ldots \cup ms_m\}.$
11: **End for**
12: **Output** $MS = \{ms_1, ms_2, ms_3, \ldots, ms_p\}$
13: **End**

Figure 4. A high-level view of the theory of minds enabled telemedicine system



Self Awareness

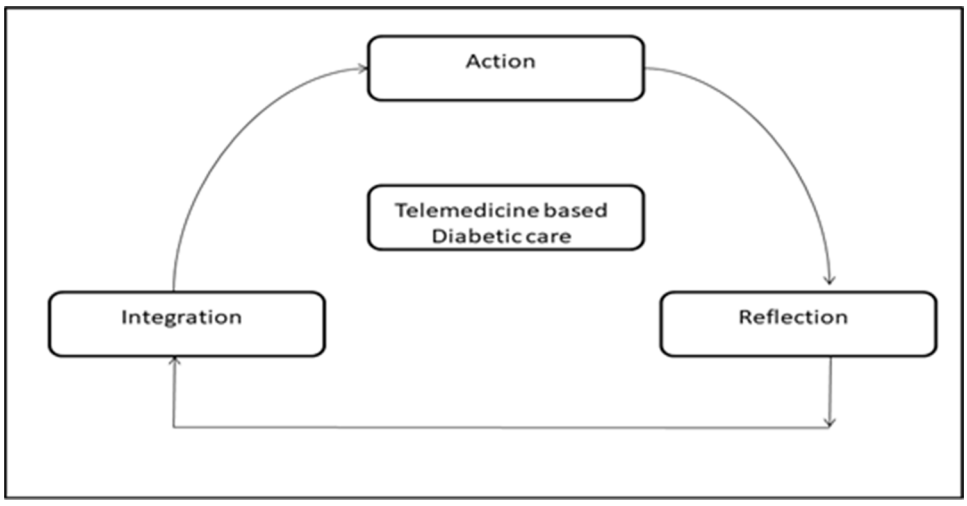
Self-awareness is the fourth form of AIT which represents an idea of being self-motivated composed of sentiments and consciousness also (Jara-Ettinger, 2019; Misra, 2019). This form of AIT is useful in performing purely hypothetical solutions to real-world problems. The self-awareness mechanism works in three stages i.e. action, reflection, and integration. The first random set of actions is performed, reflection for each action is computed then integration of each of the reflections is used to perform optimal actions. The process of arriving at the optimal set of actions is repeated in iterations to recognize the sentiment and consciousness in learning. A high-level representation of the self-awareness enabled telemedicine system for diabetic care is given in Figure 5 and detail of working is given in algorithm 4.

Some of the advantages of self-awareness are as follows improved ability in recognition, proper aligning of ideals with actions, managing relationships to elevate the emotions, self-reflection through constructive criticism, precise conversion of information to knowledge rules, overlapping information is removed, supports the proportional allocation of resources, assures reasonable system development, reduction in bias through boosting process, high level of scalability by reducing variance, provides proper insight into the existing information, the learner learns quick, high level of adaptability, cost-effective learning, a very higher degree of conceptualization, longer period of knowledge retention, computational

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power incurred is less, learned knowledge is capable of making accurate predictions, fine-tuning of actions through reflective learning, and many more (Smeresky et al., 2020).

Figure 5. A high-level view of the self awareness enabled telemedicine system



Algorithm 4: Algorithm for self awareness enabled telemedicine system for diabetic care
1: **Begin**
2: **INPUT: Actions set** $At = \{at_1, at_2, at_3, \ldots, at_m\}$
3: **OUTPUT: Integration** $Int = \{int_1, int_2, int_3, \ldots, int_p\}$
4: **# Initialization**
5: **For** each action at_i in At **do**
6: Perform action initialization $At = \{at_1 = \varnothing,\ at_2 = \varnothing,\ at_3 = \varnothing, \ldots.\ at_m = \varnothing\}$
7: Calculate reflection in X-axis $R=(x,y) \rightarrow (x,-y)$, reflection in Y-axis$= (x,y) \rightarrow (-x,y)$, where x and y are coordinates of action in action set.
8: Compute integration of reflections $Int = \int \frac{1}{\sqrt{1-R^2}} = Sin^{-1}(R)+C$, where C is the constant
9: **End for**
10: **Output** $Int = \{int_1, int_2, int_3, \ldots, int_p\}$
11: **End**

Some of the popular applications of self-awareness AIT are speech classification, identification of emotions in the human tone, performing call assistance for customer service calls, classification of emails, credit card processing through pre0defined computation, identifying the relationship between the data items in a large corpus of data, performing constrained optimization for discrete large-sized problems, reward computation for training self-sustained systems, estimation of the probability of success in multi-user games, monitoring of the multimodal working system, translation of medical notes, determining the intensions of pedestrians, developing self-driving cars with reasoning capability, and many more (Iosup et al., 2017; Sadighi et al., 2018).

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6. RESULTS AND DISCUSSION

In this section the performance achieved by the four different types of AIT in delivering diabetic care is compared towards the performance metrics like accuracy, medical error rate, speed, learning rate, throughput and makespan time using Neuroph tool which an GUI based java programming tool (Mellores et al., 2020; Vapenik et al., 2016). The performance attained is shown in Table 2. It is observed from analysis that the performance achieved by the self-awareness AIT is better towards performance metrics like accuracy, medical error rate, speed, and learning rate compared to other AITs like reactive machines, limited memory, and theory of minds.

Table 2. Performance analysis of AITs

AIT types	Accuracy	Medical Error rate	Speed	Learning rate	Throughput	Makespan time
Reactive machines	Low	Medium	Medium	Low	Low	Low
Limited memory	Medium	Low	Medium	Medium	Low	High
Theory of minds	Low	Medium	Medium	Low	Medium	High
Self awareness	High	Medium	High	High	High	Low

7. FUTURE RESEARCH DIRECTIONS

In this chapter AITs for diabetic patients, monitoring is discussed with supporting architecture and algorithms. As future work real-time implementation of the discussed AITs for diabetic patients monitoring can be done, the probability of getting diagnosed with diabetes may be predicted early with mild symptoms, and as a case study, the performance analysis of the mentioned AITs in achieving the desired level of speed and accuracy in delivering remote healthcare services can be carried out.

8. CONCLUSION

This chapter provides a brief introduction to the telemedicine-based approach for diabetic care using AIT. Four basic kinds of AITs are considered which include reactive machine, limited memory, a theory of minds and self-awareness. Each of the technique under AITs is discussed along with their architecture, algorithm, advantages, and their applications. Performance analysis of the considered AIT is carried out towards the performance metrics like accuracy, medical error rate, speed, learning rate, throughput and makespan time. It is found from the analysis that the performance achieved by the self-awareness AIT is good compared to other AIT like reactive machines, limited memory, and theory of minds.

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Chapter 21
Towards an Effective Imaging-Based Decision Support System for Skin Cancer

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ABSTRACT

The usage of expert systems to aid in medical decisions has been employed since 1980s in distinct applications. With the high demands of medical care and limited human resources, these technologies are required more than ever. Skin cancer has been one of the pathologies with higher growth, which suffers from lack of dermatology experts in most of the affected geographical areas. A permanent record of examination that can be further analyzed are medical imaging modalities. Most of these modalities were also assessed along with machine learning classification methods. It is the aim of this research to provide background information about skin cancer types, medical imaging modalities, data mining and machine learning methods, and their application on skin cancer imaging, as well as the disclosure of a proposal of a multi-imaging modality decision support system for skin cancer diagnosis and treatment assessment based in the most recent available technology. This is expected to be a reference for further implementation of imaging-based clinical support systems.

INTRODUCTION

Skin cancer is a fast-growing health concern and threat for humans. Its diagnosis is still a challenge, and when made early, eases the consequences with appropriate treatment. Since 1980's technology has incrementally been adopted in daily medical practices to help in the management of health professionals, promotion of better care and aid in diagnostic procedures. Since skin cancer is thriving and the number

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of specialists is limited, the demand for an effective decision support system (DSS) to ease the burden of the existing experts is high.

This chapter is organized by presenting the problem of skin cancer, its types, the traditional diagnosis and treatment options, the promising imaging technologies that can facilitate a differential diagnosis, the existing freely available datasets that can be used for research, a review on the application of decision support systems in the skin cancer diagnosis, the proposal for an implementation of a generic effective DSS for skin conditions and remarks with a critical discussion and conclusion.

This research aims to present the current diagnosis and treatment options for skin cancer, the existing promising imaging technologies to improve it, disclose the existing free datasets for research, review the application of DSS in skin cancer and propose a generic technologically advanced effective DSS for skin conditions management.

BACKGROUND

Like any other cell in the human body, skin cells are subjected to different types of mechanisms that regulate their development and replacement, if considered needed.

Typically, physiological pathways are triggered to induce apoptosis of malfunctioning cells and destroy it before causing harm. If these defense mechanisms fail, the defective cell can grow out of control and generate a skin neoplasm. (Hunter et al., 2002a)

An abnormal cell grow is not inevitably indicative of the appearance of a cancerous tissue. Benign or malignant tumors can arise, and its differentiation should be clarified. Malignant masses are generally referred to as cancers and are histologically characterized by cells considerably dissimilar from the ones of its mother-tissue. There is a clear tendency to grow and multiply at an excessive rate, as well as to eventually infiltrate neighbor tissues and close-by vascular and lymphatic structures. This feature, i.e., metastization, allows it to spread to different organs and originate a new tumor focus, complicating its treatment and increasing the associated life-risk. Contrarily, benign neoplastic cells tend to be somewhat like its tissue of origin, presenting decent cell differentiation. Their growth rate is considered slower when compared to malignant ones, and the ability to metastasize is absent. In fact, these tumor types have a tendency towards local expansion, pushing adjacent structures. Thus, normally, it does not represent a threat for its host. (Crowley, 2013; L Kemp et al., 2015)

Anatomical changes are guaranteed to happen with the emergence of a tumorous mass. Still, the occurrence of physiological shifts is far more relevant, especially if in the presence of a cancerous lesions. (Baba & Catoi, 2007a) Contrarily to what most could hypothesize, the neoplastic mechanisms are not uniquely controlled by genes that underwent mutations. Genes that retained its "normal" structure can have a detrimental influence, as the promotion of the expression of proteins, normally included in regular cellular processes, but at inappropriate occasions and with the inappropriate extent. Thus, enhancing carcinogenesis. (Moasser, 2014)

At the beginning of neoplasm development, the tumor possesses low metabolic requirements than what could be expected. Still, to guarantee a continuous and interrupted growth, its constituent cells disseminate angiogenic growth factors (e.g., vascular endothelial growth factors (VEGF)) to avoid vasoconstriction and subsequent cancellation of blood supply. (Baba & Catoi, 2007b; Moasser, 2014) As cells multiply, eventually oxygen and nutrient deplete and neovascularization takes place, originating new blood vessels within the tumor. Blood perfusion is also triggered, by the neuronal messenger nitric

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oxide, as it provokes vasodilation of surrounding vessels. All in all, boosting incessantly neoplastic growth and proliferation (Moasser, 2014).

The mutations responsible for the appearance of a skin cancer, can have exogenic and/or endogenic causes. Fitzpatrick skin phototype, hair, eye, and skin color, family history of skin cancer and excessive number of moles are all individual' traits that can suggest a person' predisposition for the development of the disease. For exogenic causes, contact with chemically aggressive elements, as arsenic, is an option. Though, excessive exposure to ultraviolet radiation is the most dangerous exterior cause, causing not only DNA defects on epidermal cells, but also the death of macrophages (Langerhans cells) responsible for the detection and elimination of malfunctioning ones. Based on the malignant mutations that take place, different types of skin cancers can arise and affect/infiltrate different skin layers, from epidermis to dermis and even subcutaneous fat (Hunter et al., 2002b; Gordon, 2013; Carr et al., 2020).

Distinction of Melanoma and Non-Melanoma Skin Cancer

Despite sharing a common trigger-feature, i.e., the occurrence of a malignant mutation on skin cells, skin cancer takes several forms according to the mutated skin cell type. Normally, cancerous skin tumors are divided as melanoma and non-melanoma skin cancer. The latter encompasses squamous cell carcinoma (SCC), basal cell carcinoma (BCC) and Merkel cell carcinoma.

Before detailing each skin cancer type, it is worth to know that some "benign" skin neoplasms may be categorized as precursor lesions, if its existence is latter connected to the growth of malignant neoplasms. Keratocyte tumors, as thermal, tar or arsenical keratoses, depending on the mutagenic agent, are included in this group. Though, the most common of all is actinic keratosis (AK). (Fernandez Figueras, 2017) AKs are normally found in body areas frequently exposed to sunlight, hence, UV radiation is considered the critical etiological factor. It is represented by a papule with a gradient color from skin-tone to a brownish-yellow tone (Fig. 1). Histologically, AK are inflammations of the dermis combined with a proliferation of dysplastic keratinocytes in the epidermis, giving it a scale-like appearance that is rough to the touch. Its progression can lead to the malignant type of skin neoplasms: SCC. Nevi, benign melanocytic lesions, that present a dysplastic showing of melanocytes are also an increased risk for the development of skin cancer, in this case, melanoma. (Kang et al., 2019; Marks & Miller, 2019a)

As mentioned, skin cancer can be classed as melanoma and non-melanoma.

The first type is the deadliest form of all, particularly if detected at an advanced stage of development. As its benign "brother", i.e., nevi, it arises from an abnormal proliferation of melanocytes. Yet, its major disparities, lie on visual attributes. Melanomas are known to present considerable changes in size in shorter time intervals, being this growth accompanied by an amorphous contour with a combination of a variety of different pigmentations from brown tones to black (Fig. 1). Its differentiation from nevi is particularly difficult when at early stages of development. Despite with lower incidence than non-melanoma skin cancer, it possesses a high death rate associated to it (Table 1), due to its capability to metastasize, spreading malignant melanocytes to other organs to create additional cancerous sites. (Kang et al., 2019; Marks and Miller, 2019b; Ricotti et al., 2009; Schwartz, 2008a).

The non-melanoma type squamous cell carcinoma is one of the most common forms of skin cancer. Its development is often linked to pre-existing lesions, e.g. keratoses, having a greater malignant potential when from thermal, tar and arsenical dysplasia's. An over-proliferation of keratinocytes fuels its expansion, having a clear tendency to infiltrate the dermis, while retaining the ability of keratin production. Normally, SCC invade its host tissue and only multiply into its surrounding healthy skin. Still, some

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Table 1. Incidence and mortality numbers of melanoma and non-melanoma skin cancer for world population during the year of 2020.

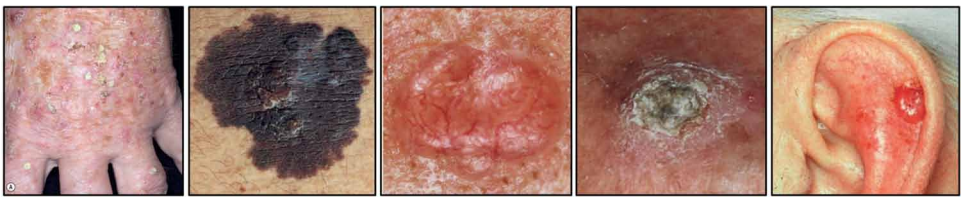
		World
Incidence	Melanoma	324 635
	Non-melanoma	1 198 103
Mortality	Melanoma	57 043
	Non-melanoma	63 731

tumors can grow in several directions and even metastasize. In terms of anatomical features, it is somewhat like AK tumors, but with greater size and thickness, with a protuberant growth that can originate a horn-like structure (Fig. 1) (Hunter et al., 2002a; Ricotti et al., 2009; Schwartz, 2008b).

Basal cell carcinomas are constituted by aggregates of basal cells that proliferate into the dermis. It is usually a local infiltrator as SCC, presenting several forms. The most common one is noduloulcerative, followed by superficial, morpheaform and pigmented. The first possesses a node-like structure with a dome that frequently ulcerates. Superficial BCC and morpheaform are usually quite similar, being the first a more pinkish, well demarked structure while the second one can seem like scar tissue (Fig. 1). As the name implies, pigmented BCC is characterized by a heavily pigmented papule and can sometimes be confused with a melanoma tumor (Kang et al., 2019; Ricotti et al., 2009; Schwartz, 2008c).

The last type is not as frequently diagnosed as its associates. Still, Merkel cell carcinoma presents a life risk 2 to 3 times higher than melanoma. The mutated Merkel cells originate a pink/purplish nodule that assimilates to an insect bite (Fig. 1). It is fast growing, and commonly late detected, so spreading to additional organs is plausible to happen (Schwartz, 2008d).

Figure 1. Examples of pre-cancerous and cancerous skin neoplastic lesions. From left to right: AK, melanoma, BCC, SCC, Merkel cell carcinoma.



Current Diagnosis

Nowadays, it is fair to say that the gold-standard procedure for diagnosis of skin neoplasms is composed by two stages: visual assessment and histological identification.

The first has remained almost unaltered over the years, being based on a visual examination performed by a physician, as a dermatologist or plastic surgeon. Lesion anatomical traits are essential here, as well as patient description of lesion behavior over time (e.g. size alteration, bleeding, shape variation) . Usually, a Dermoscopy device is utilized by clinicians to have a better visualization of lesion charac-

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teristic features invisible to the unaided eye. Also known as skin surface microscopy, epiluminescence microscopy or incident light microscopy, this non-invasive technique uses, at least, 10-fold magnification to facilitate the observation of shape, vascular structures, and color patterns from the epidermis to the upper dermis. Lesion is normally covered with a liquid medium (e.g. water, alcohol) to prevent the appearance of reflection artefacts, unless the system includes a polarized light source. Different gadgets can be used, as handheld dermoscopes, that are cheaper but present low magnification capacity, or digital dermoscopies, more expensive but with greater amplification and the possibility of image storage for lesion comparison over-time. Though, it can also be of assist for evaluation of lesions with little to no pigment, this tool is normally used for the assessment of pigmented lesions. When in the presence of the latter, the observer first distinguishes melanocytic (melanoma, melanocytic nevi) from non-melanocytic ones (e.g., pigmented BCC, angioma, seborrheic keratosis). Then, a preliminary diagnosis is reached based on lesion' characteristics. In the case of melanocytic neoplasms, different methods can be used for visual inspection, as the ABCDE rule, Menzies method and 7-check-point list. The first strategy is normally preferred. The physician assesses lesion Asymmetry at different axis, followed by the evaluation of neoplasms Borders to check for unexpected terminations of pigmentation throughout lesion' contour. Then, the presence of different Colors is validated, as well as the existence of Differential structures (brown globules, dots, pigmented network, streaks). Finally, lesion Evolution is analyzed, either by previous registries with digital Dermoscopy or by patient report (Fig 2). A positive assessment for each one of these characteristics, strongly indicates the presence of a malignant melanocytic lesion, i.e., melanoma (Kato et al., 2019; Schwartz, 2008e, Yélamos et al., 2019). Despite, being the preferred technique for skin cancer assessment, Dermoscopy accuracy is highly dependent of physician experience and training. Thus, teaching and practice regarding its use is extremely necessary, to take profit from it, during patient diagnosis (De Bedout et al., 2021; Fee et al., 2020).

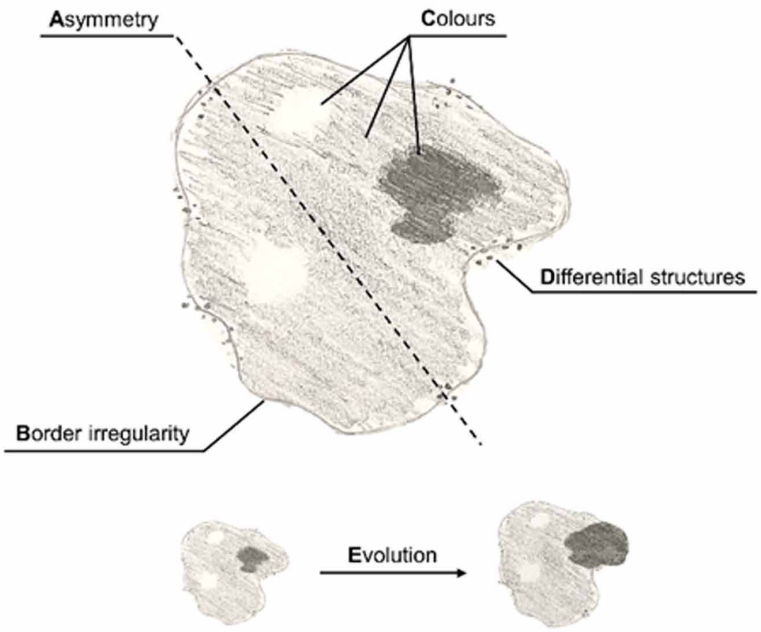
When there is uncertainty regarding the malignancy of a skin tumor, a biopsy procedure is usually scheduled to remove it entirely (excisional) or partially (incisional) and confirm diagnosis. In incisional procedures, i.e., needle or punch biopsy, only a small sample of the suspicious neoplasm is removed for histopathological analysis. It is only preferred when the lesion is considerably large and/or located in a sensible area, as face. Yet, it is not widely used due to the idea that the technique can disrupt malignant cells to adjacent tissue, promoting metastization.

Surgical excision can be executed with several techniques. The most traditional one, simply involves lesion removal with an elliptical excisional margin that can vary from 1 to 6 plus mm, followed by a biopsy. When tumor is diagnosed as malignant, additional skin margins needs to be removed and analyzed, to guarantee a tumor-free margin. Thus, several surgeries might be needed. To avoid this, the use of Mohs' micrographic surgical technique is preferred, as it allows a thorough histopathological analysis of the neoplasm' edges during the procedure. As skin tissue is excised, the surgeon performs a microscopical analysis of the removed tissue and performs additional re-excisions of the remaining neoplasms until a tumor-free margin is attained. Thus, allowing, a maximal preservation of healthy tissue while removing the cancer completely.

Despite being a very precise strategy, the gold-standard procedure for skin cancer lesions possesses several downfalls. The experience dependency associated to the Dermoscopy stage is the first hurdle, being this half the battle to determine a correct diagnosis or highly imprecise analysis. The biopsy stage involves consequences and disadvantages, as patient' suffering and discomfort, sometimes deemed unnecessary. The produced wound can cause cosmetic imperfections, like scarring and bruising, as well as infections, depending on its size and postoperative care. Additionally, the time gap between the surgical

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Figure 2. Scheme of melanocytic lesion assessed with ABCDE rule: asymmetrical lesion, irregular borders, presence of three different shades of color, presence of differential structures, e.g., brown globules, dots, pigmented network, and lesion evolution over time.



procedure and the release of biopsy results can encompass several weeks, increasing stress associated to diagnosis (Doolan et al., 2019; Hoorens et al., 2019; Weinstein et al., 2017; Yagerman and Stevenson, 2018).

To avoid the performance of unnecessary biopsies, as well as the failure of not carrying histological examination when needed, complementary diagnosis techniques with a non-invasive approach are of clinical interest. Always with the goal of maximizing diagnosis accuracy, while being cost-effective and patient thoughtful.

Treatment

Different treatment modalities are offered for skin cancer lesions. After a primary evaluation, it is up to the physician to define the best course of actions based on lesion size, site, invasiveness and metastatic potential and anatomical and physiological features. The optimal treatment is always the one that eliminates malignant cells while favoring the best cosmetic outcome.

Excisional surgery is probably the most frequent treatment prescribed, as it serves two purposes: lesion removal and pathological analysis. Though, as previously mentioned, sufficient margins are needed for success, which can be difficult in certain body areas as eyelids, nose, and ears. If not possible, alternative treatments should be considered to avoid recurrences and subjection of patient to unnecessary pain and

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scaring. From the available options, performance of lesion excision is always preferred with Mohs technique to guarantee minimal disfiguring while maximizing margins (Schwartz, 2008; Shriner et al., 1998).

For other treatment alternatives, topical chemotherapy is particularly of interest when dealing with large regions affected by actinic lesions. Topical agents as retinoids, diclofenac and topical 5-fluorouracil are applied to the neoplasm for a prescribed period, eliminating completely or partially the tumors. It has the advantage of being a localized treatment, as oppose to traditional (systemic) chemotherapy, thought the leased skin tends to be extremely delicate and tender for a period after treatment (Sahu et al., 2019; Orthaber et al., 2017; Simoes et al., 2015). A similar approach is followed in photodynamic therapy, where a topical agent is applied to the tumorous area, accumulating in cancerous cells. Later, the region is irradiated with a light source to induce the production of reactive oxygen species toxic to the target tissue. In some cases, the topical agent might be substitutes by a drug administrated via blood stream or in the form of a tablet, depending, per example, on lesion size or location. It is usually faster and less aggressive than excision, being the main side effect a burning sensation, normally tolerable (Kapek et al., 2020; Papakonstantinou et al., 2018) Another light-based method is laser therapy, only used for pre-cancerous lesions and small malignant neoplasms. A high intensity narrow beam, e.g., CO_2 laser, irradiates and destroys the tumor, in a very precise manner, thus delivering a good cosmetic outcome. (Soleymani et al., 2017; Mirza and Khatri, 2017). Tumor destruction is also attained with cryosurgery. Cryogenic agents at extremely low temperatures, typically liquid nitrogen, are used to induce necrosis of a specific skin area through freezing of its constituent cells. It is not indicated for deeply penetrating tumors and usually not preferred for melanoma treatment. Caution also needs to be taken if implementing it in patients with Fitzpatrick 5 skin type, as hypopigmentation may occur following the treatment. (Pasquali, 2015; Buckley et al. 2020) When dealing with small skin cancers, curettage and electrodesiccation is usually chosen by most physicians. As the name indicates, the tumor is curetted, and an electrode is used immediately after on its edges to kill neoplastic cells that remained outside the curetted area. The process of electrodesiccation is completed when no tumor is visible, being very effective. Though, wound healing should be carefully controlled to avoid infections. Lastly, radiotherapy is usually applied as and adjuvant technique to other treatments for metastatic or highly invasive tumors, and never as a solo treatment option (Goldman, 2002; Lin et al. 2019).

Emerging Non-Invasive Diagnostic Technologies for Skin Cancer

Innovations on the field of skin cancer detection occur as a way of fighting deficiencies of current approaches. When lesions are detected early, better prognosis is projected, so new tools that assist in this task are attractive to improve patient' survival rate. Particularly, innocuous methods have gain interest and attention, as more and more, non-invasive treatment options are preferred to traditional approaches, to reduce scarring and avoid highly disfiguring outcomes.

Several adjunct tools, beyond visual assessment, have been investigated. Certain techniques have already been applied in a different clinical setting and are now exploited as a potential tool for skin cancer diagnosis (Table 2).

Ultrasounds are widely used as a diagnosis tool for numerous pathologies since the 1950's. The emitted sound waves allow the assessment of structures' heterogeneity within the body based on different echogenic properties. The application of High Frequency Ultrasonography (HFUS) refers to the use of an ultrasound probe that emits waves with frequencies above 10MHz. The shorter wavelength waves are rapidly absorbed and do not reach deeper tissues, delivering images with improved resolution of

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upper skin layers. Thus, allowing its effective application in the dermatological field. For skin tumor diagnosis, the assessment of characteristic inner components is possible and can even assist surgery as it exposes tumor invasiveness. For melanomas, it has been reported a lower rate of echogenicity, contrarily to benign neoplasms, allowing a clear detection of tumor margins (Botar-Jid et al., 2016). Other skin malignancies, as BCC, follow the same line, showing hypoechoic patterns when compared to its surrounding tissue (Barcaui et al., 2014). Its non-invasiveness and appealing price make it attractive for skin neoplasms evaluation. Though, its sensitivity is limited when used to evaluate ultra-fine tumors (Wortsman and Wortsman, 2010) or extremely thick ones (Mandava et al., 2012). Additionally, it is an operator-dependent technique, as Dermoscopy, requiring extensive training for good diagnostic performance (Zmudzinska et al., 2008; Polańska et al., 2017; Zheng, 2005; Catalano et al., 2019).

The characterization of skin tumors can also be performed through Confocal Scanning Laser Microscopy (CSLM). A low-power laser beam strikes a focal skin point, after passing through a lens. The reflected light is detected as an electrical signal and ultimately translated into grayscale images. The images can depict different histopathological features and associate it to distinct types of skin tumors, being something referred to as an "optical skin biopsy". For the most aggressive form of tumor, i.e., melanoma, CSLM assists in its diagnosis through the visualization of atypical melanocytic cells in the epidermis, particularly in patients with many melanocytic lesions or with potentially cancerous tumors that do not follow the common ugly duckling traits. (Carrera et al., 2012; Rajabi-Estarabadi et al. 2019) Different traits characteristic of BCC have been specified in CSLM, with basal cells appearing as bright spots encircled by darker holes. These findings have been correlated with histopathological results (Que et al., 2015; Lupu et al., 2014). The assessment of both SCC and AK tumors has proven to be challenging, as images often appear mostly white, due to the great amount of reflection caused by tumor structures filled with keratin. Its distinction is more easily done when tumorous cell aggregates are found on the dermis (Que et al., 2015; Aghassi et al., 2000). The greater advantage of CSLM over Dermoscopy is the ability to detect melanoma lesions that do not present the typical features described by the ABCDE rule. Additionally, it aids in estimation of excision border and tumor recurrences, as well as treatment monitoring. Despite its advantages, it is very expensive, a bit time-consuming and demands expertise for its application, complicating its dissemination in a hospital setting (Parsons et al., 2011; Ilie et al., 2019:).

Optical Coherence Tomography (OCT) appears as an imaging modality that offers cross-sectional images of subcutaneous tissue with the use of scattered and reflected infrared light. Conventional equipment possesses a penetration depth of 2 mm, while high-definition OCT can go down to 0.57 nm, allowing the visualization of single cell units. Its application for skin cancer evaluation is well-studied for BCC diagnosis, as well as the assessment of neoplasm border during Mohs, reducing the possible cosmetic defect (Hussain et al., 2015; Chan and Rohrer, 2012) For pigmented lesions, nests of atypical cells close to the dermis haven been documented in higher quantities for melanoma tumors when related to benign melanocytic lesions (Gambichler et al., 2015). In regards of SCC, a clear thickening of the epidermal layer is present, though its differentiation from AK remains challenging, as with CSLM. (Reggiani et al., 2015) The advantages of OCT, include real-time assessment of skin tumor morphology the need to remove any tissue sample, as neoplasm is scanned laterally with the light beam. Despite presenting a penetration depth inferior to that of US, it shows greater resolution and does not require physical contact with the specimen. It presents lower resolution than CSLM and its efficiency can also be affected by tumor thickness (Ferrante di Ruffano et al., 2018; Levine et al., 2017).

Adhesive patch biopsy (APB) is the closest approach to a traditional biopsy procedure. Yet, without the pain and scaring involved. It is the only innovative method, presented here, that is not image based.

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The outermost skin layer, i.e., stratum corneum, is removed with the aid of adhesive tape pressed onto the lesion site. RNA from the harvested cells is analyzed to detect specific gene profiles and differentiate, mostly, pigmented skin lesions. This technique rests on the idea that mRNA is scattered to this skin layer by melanocytes through the same channels as melanin is. When combined with visual assessment using ABCDE rule it can improve diagnostic sensitivity and specificity, allowing the early identification of melanomas, though several sample stripping might be needed. (Gerami et al., 2014; Hughes et al., 2021; Fried et al., 2020).

The 3D imaging of epidermal and upper-dermal structures is feasible with Multiphoton Laser Scanning Microscopy (MPLSM). Endogenous fluorophores present in skin neoplasms, emit a fluorescence signal after two-photon excitation, normally with near infrared light. The autofluorescence images present high resolution, allowing the study of melanoma and non-melanoma lesion with high sensitivity and low light damage. Different morphological features were found for SCC and superficial BCC, as the presence of hyperkeratosis and palisading of cancerous cells, respectively. (Paoli et al., 2008) For melanoma lesions, it has recently shown its usefulness for the identification of sentinel lymph nodes (Kantere et al., 2020). When compared to CSLM it has a higher penetration power, though if the lesion is considerably thick, out-of-focus fluorescence can interfere with the collected images (an issue non-existent in CSLM due to the use of a pinhole) (Paoli et al., 2009; Multiphoton Excitation and Microscopy, 2006).

Different tissues present different properties, and electrical impedance is no exception. The technique of bio-electrical impedance (BEI) uses a spectrometer to quantify this property at different frequencies. The measured current is influenced by water content of the assessed tissue, varying when cells endure malignant mutations. This technique has already been applied for the diagnosis of melanoma and BCC with good diagnosis metrics. The acquired impedance spectra delivered sufficient information to distinguish benign nevi from melanoma (80% specificity and 92% sensitivity) and basal cell carcinoma (86% specificity and 96% sensitivity) (Aberg et al., 2005). This technique has also been successfully implemented for the monitoring of melanoma scars after surgery. The property of bio-electrical impedance can be measured on the excision site, to monitor and guide a proper tissue regeneration stage (Logothetis et al., 2019). Apart from complementing data collected from dermatological examination, one of its great advantages is that it can be carried out multiple times to perform lesion surveillance throughout time. Still, specificity is not great, keeping biopsy numbers elevated.

Infrared thermal (IRT) imaging is the only emerging method that does not require direct contact with the patient or irradiation with light sources to assess skin tumors. This technique exploits the capability of the human skin to irradiate infrared heat naturally and continuously, capturing it with thermal cameras. Distinct temperature patterns are expected from unadulterated skin tissue when compared to neoplastic regions, with increased metabolic and vascular activity, and consequently, heat dissipation. Practical studies are found for the identification of thermal patterns characteristic of melanoma and nevi, with melanoma presenting higher temperature values than healthy skin tissue (Magalhaes et al., 2019). When stimulation is included, i.e., dynamic implementation instead of a static approach, by mechanical, chemical, or thermal means, this difference is accentuated, easing skin tumor identification (Pirtini Çetingül and Herman, 2011). Additional skin lesion types, as BCC, SCC and AK have also been analyzed with IRT imaging to adjuvant diagnosis (Baek et al., 2019; Godoy et al., 2017) The main set-back of this technique concerns the need of a controlled environment, to guarantee correct temperature measurements (Ammer, 2003; Ring and Ammer, 2015; Ring and Ammer, 2012).

Another technique, not widely used on day-to-day practices, is photodynamic diagnosis (PDD). This methodology consists of the application of topical agents onto the lesion, followed by excitation with

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a light beam to stimulate the production of photosensitizers. These fluorescent compounds present a greater accumulation rate on skin neoplasms compared to healthy skin. PDD is recent for skin cancer applications, but surely promising. Its recent use is found for the diagnosis of metastatic melanoma. (Naidoo et al., 2019) Due to the induction of the production of fluorescent compounds, it is a very helpful tool to guide tumor' excision, while being non-invasive and extremely target-precise. Thought, PDT is not without limitations as it cannot be applied to patients with specific blood diseases (Krammer and Verwanger, 2016; Lipiński et al., 2015).

Ultraviolet (UV) imaging can be considered the most recent technique for skin cancer assessment. Its application presents two variants with reflected-UV imaging and fluorescence-UV imaging. The first involves the use of an UV excitation source that results in the acquisition of an image representative of the UV radiation reflected at the same wavelength by the irradiated object. In the case of the second, a UV light is used as an excitation resource to promote the reemission of longer wavelength rays, often in the visible area of the electromagnetic spectrum. Thus, it is passible of being imaged with a standard digital camera. Though, recent, UV fluorescent photography has been indicated as a valuable tool for the evaluation of tumor margins in BCC cases, while UV reflectance has shown good input in the appraisal of skin photoaging (Mojeski et al., 2020; Crowther, 2020; Pratt et al., 2017).

Table 2. Emerging non-invasive techniques and its associated advantages and drawbacks.

Technique	Advantages	Drawbacks
High frequency ultrasonography	Evaluate tumor invasiveness Aid with excision planning	Low sensitivity for very thin/thick melanomas User-dependent
Confocal scanning laser microscopy	Diagnose melanoma in absence of Dermoscopy features Assist in estimation of excision border Non-invasive treatment monitoring Detection of tumor recurrences Surveillance of lesions over time High sensitivity and specificity	Very expensive Time consuming Demands expertise
Optical coherence tomography	Assist in estimation of surgical borders Contactless Higher resolution than HFUS High sensitivity and specificity	Lower resolution than CSLM Performance affected by tumor thickness
Adhesive patch biopsy	Reduce number of biopsies No-scarring Early diagnosis of melanoma	Multiple stripping might be needed Destined for melanocytic lesions
Multiphoton laser scanning microscopy	High resolution High sensitivity Low light damage High penetration power than CSLM	Poorer resolution for thicker lesions Excitation wavelength needs to be refined to guarantee fluorescence while innocuous for the tissue
Bio-electrical impedance	Assist in estimation of surgical borders Surveillance of lesions over time	Low specificity Poor performance in given body areas
Infrared thermal imaging	Contactless Real-time measurement Cost-effective (when compared to other imaging modalities) Surveillance of lesions over time	Need of controlled examination room conditions
Photodynamic diagnosis	Extremely target-precise Assist in estimation of surgical borders	Not suited for patients with specific blood diseases
Ultraviolet imaging	Evaluation of tumor margins Contactless	Extremely expensive equipment Need for artificial light sources

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Existing Freely Available Skin Cancer Datasets

To date there were only found 7 freely available skin cancer datasets through a search on the main repositories of data, Kaggle (https://www.kaggle.com) and UC Irvine Machine Learning Repository (https://archive.ics.uci.edu/ml), which are characterized on table 3.

Table 3. Freely available skin cancer datasets.

Dataset name	Data type	Samples (N)
ISIC 2019 challenge	Images and 15 attributes	25331
Dermnet	Images and diagnostic	19500
HAM10000	Images and 7 attributes	10015
Melanoma Image Data (U.Porto)	Images and 15 attributes	435
SKINL2	Images and diagnostic	376
Dermoscopy Skin Lesion Multispectral Image Database	Images and diagnostic	30
Dermatology Data Set	34 attributes	336

The ISIC 2019 challenge dataset (ISIC, 2019) contains 25,331 (2017 and 2018 are also included) images available for the classification of dermoscopic images among nine different diagnostic categories: Melanoma, Melanocytic nevus, BCC, AK, Benign keratosis, Dermatofibroma, Vascular lesion, SCC and None of the previous. It has a total of 15 attributes consisting of the beforementioned categories, patient age, sex, lesion anatomical location, lesion id and image reference.

The Dermnet (Dermnet, 2020) dataset is composed of 19500 images of 23 types of skin diseases. All images are in JPEG format with 3 color channels, e.g. RGB, with variable resolution. The lesion categories include acne, melanoma, Eczema, Seborrheic Keratoses, Tinea Ringworm, Bullous disease, Poison Ivy, Psoriasis, Vascular Tumors.

The HAM10000 ("Human Against Machine with 10000 training images") dataset (Tschandl et al., 2018) consists of 10015 dermatoscopic images of pigment lesion released for academic research involving machine learning methods. Along with the images there are 7 attributes: image id, lesion id, diagnostic, diagnostic type, patient age, patient sex, and lesion anatomical location. More than 50% of the sample include histology results, lesion included in the database are: AK, BCC, benign keratosis-like lesions, dermatofibroma, melanoma, melanocytic nevi, and vascular lesions.

At the University of Porto there it was developed a project of a melanoma PH^2 dataset (Mendonça et al., 2013), which is composed of a total of 200 dermoscopic images of melanocytic lesions, including 80 common nevi, 80 atypical nevi, and 40 melanomas. All images have a magnification of 20x and are 8-bit RGB color images with a resolution of 768x560 pixels. It also includes attributes such as: clinical diagnosis, asymmetry, pigment network, presence of dots, streaks, regression areas, presence of blue whitish veil and mention of all colors present at the lesion.

Another dataset also developed in Portugal, the light field dataset of skin lesions (SKINL2) (Faria et al., 2019) consists of 376 plenoptic camera with extended depth of field images, which were categorized

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as melanoma, melanocytic nevus, BCC, seborrheic keratosis, hemangioma, dermatofibroma, psoriasis and other.

The Dermoscopy Skin Lesion Multispectral Image Database (Lézoray et al., 2014) has 30 multispectral dermoscopic images with resolution 800x600 and are composed of 6 spectral bands (3 in visible spectrum light and 3 in infrared light).

The Dermatology Data Set (Güvenir et al., 1998) has 336 samples of 34 attributes, being 12 clinical and the remaining histopathological. It also includes the patient demographic data and his family history. The skin conditions present at the database are psoriasis, seboreic dermatitis, lichen planus, pityriasis rosea, cronic dermatitis, and pityriasis rubra pilari.

It can be observed that all freely available datasets are of a single nature of data, being a multispectral imaging dataset with clinical, histological, patient and family record multisource dataset missing.

Existing Skin Cancer Decision Support Systems

Since the general application of clinical DSS in the mid 1980's, they spread from general to specific applications, in this section attention will be given to the Skin Cancer oriented DSS, which were retrieved from literature sources such as PubMed and Scopus after screening the abstracts.

The aim of the clinical DSS is to be able to process more data and achieve a better sensitivity, and specificity than human experts, dermatologists, trainee, and general practitioners (table 4).

Table 4. Average sensitivity and specificity of human experts, dermatologists, trainee, and general practitioners (Przystalski et al., 2010).

	Sensitivity	Specificity
Expert	90%	59%
Dermatologist	81%	60%
Traine	85%	36%
General practicioner	62%	63%

A melanoma DSS was implemented using 152 Dermoscopy images with features extracted from ABCDE rule and texture segmentation and a multi-classifier with a combination of LDA, Decision Tree and kNN with a voting system for the best result achieved 81% sensitivity and 74% specificity (Sboner et al., 2003).

A performance of a spectrophotometric DSS system based in ANN involving 1794 samples was tested, achieving a sensitivity of 88% and a specificity of 80%, recognized 95% of the cutaneous melanoma cases. The ANN training procedure was based on the backpropagation and conjugate gradients algorithms. The images acquisition consisted of images at 15 different spectral bands (30 nm bandwidth) between 483 and 950 nm. Having the images, a useful area of 18×14 mm^2 (spatial resolution of 33 pixels mm^{-1}) (Carrara et al., 2007).

A melanoma DSS using 2851 dermoscopic images based in the ABCD rule and ANN showed a sensitivity of 75% and specificity of 84%, which was lower than achieved by experts that was 97% and 93% respectively but analyzed much less samples (Dreiseitl et al., 2007).

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A skin cancer DSS system composed of 110 Dermoscopy images using a ABCDE rule, achieved an accuracy of 92.15% on the cooperation of a NB and MLP-7 classifiers (Ruiz et al., 2008).

Using 152 images from the Dermnet dataset consisting of 55 features of the ABCDE rule and texture classified with NB model achieved 86% accuracy. This model also used age, skin type, lesion location and sex as features (Alcón et al., 2009).

An automated Content-Based Image Retrieval (CBIR) system for the diagnostic of dermoscopic images of pigmented skin lesions consisting of 24804 dermoscopic images corresponding to 20491 pigmented lesions with known pathology, using the ABCD rule, a hierarchical multi-scale computation of the Bhattacharyya distance and SVM classifier achieved a maximum precision of 94.1% in the benign nevi identification (Baldi et al., 2009).

The best result was obtained for linear SVM – 97.44% for 70/30 train to test ratio on 5189 color dermatoscopic segmented images (Przystalski et al., 2010).

A Melanoma DSS consisting of 187 samples of Multiple-Scattered Light Spectroscopy (MSLS) images achieved 89% sensitivity, 89% specificity, and 89% accuracy with NB (Li et al., 2014).

A computer-aided diagnosing (CAD) system was developed for skin cancer diagnosis consisting in pre-processing, segmentation, features extraction and classification using Self-advisable SVM on 168 dermoscopic images based in the ABCD rule achieved an 90% accuracy with 91% sensitivity and 89% specificity (Masood et al., 2014).

A CAD for melanoma diagnosis based in color analysis and probabilistic model Correspondence-LDA of 482 Dermoscopy images and classified with an AdaBoost algorithm achieved an average precision of 84.9% (Barata et al., 2015).

One DSS based in 200 dermoscopic samples used a classifier based in self-advised SVM with a radial basis function and presented an accuracy of 89% (Masood et al., 2015).

A dataset composed of 160 ultrasound images with parameters selected according to Mahalanobis distance and linear SVM classification, was able to differentiate malignant from benign melanoma presenting 82.4% accuracy (Andrėkutė et al., 2016).

Using feature selection with a Genetic Algorithm for classification with kNN on a database composed of 167 fluorescence images achieved an accuracy of 94% (Odeh & Baareh, 2016).

A DSS using a classifier composed of Deep Learning based ANN and Hybrid Adaboost-SVM algorithms in a database of 992 Dermoscopy images presented an accuracy of 93% (Premaladha & Ravichandran, 2016).

Using a ABCDE rule were applied to Genetic Algorithms for feature selection and classification with SVM on 1300 Dermoscopy images achieved an accuracy of 88% (Tan et al., 2016).

A multicenter DSS for discriminating Melanocytic Nevi from Malignant Melanomas using a training database of 1300 samples achieved an accuracy of 94.1% using a ABCD rule input to an ANN (Kostopoulos, 2017).

To a dataset containing 200 Dermoscopy 8-bit RGB channel images at 768x560 resolution, a classification was applied using ANN, SVM, kNN and DT based in the parameters of ABCD rule assessment presented an accuracy of 92.50%, 89.50%, 82.00% and 90.00% respectively (Ozkan & Koklu, 2017).

A classification of the skin cancers using ECOC SVM with deep convolutional neural network on a total of 3753 images achieved a maximum average accuracy of 95.1% for SCC (Dorj et al., 2018).

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Histogram analysis and segmentation parameters of 294 images were processed and selected as input to ML methods, which were compared, and the best achieved result was of RF with 77.26% accuracy (Gautam et al., 2018).

A DSS for detection and localization of Cutaneous Vasculature in Dermoscopy images using a database of 200 images having shape, size, color and architecture vascular features classified with data-driven feature learning framework based on stacked sparse auto-encoders (SSAE) presented 91.1% accuracy (Kharazmi et al., 2018).

Using the ISIC 2017 skin lesions images database composed of 2000 samples, a DSS with ABCDE rule and texture features classified using SVM achieved a 93.95% accuracy (Saleem, 2019).

A hyperspectral imaging DSS employing 125 spectral bands captured between 450 and 950 nm used a database of 76 images with features labeled using Spectral Angle Mapper algorithm and classified with a SVM Linear classifier presented 89% accuracy (Leon et al., 2020).

At table 5, the existing skin cancer DSS sensitivity and specificity values can be observed that only six outperform the expert sensitivity, but all overachieved the general practitioner sensitivity. In terms of specificity all published DSS present better performance when compared with human experts, dermatologists, trainees, and general practitioners.

Table 5. Sensitivity and specificity reported for existing skin cancer decision support systems.

	Sensitivity	**Specificity**
Sboner et al. 2003	81%	74%
Carrara et al. 2007	88%	80%
Dreiseitl et al. 2007	75%	84%
Ruiz et al. 2008	79.13%	93.72%
Alcón et al. 2009	94%	68%
Li et al. 2014	89%	89%
Masood et al. 2014	91%	89%
Barata et al. 2015	78.9%	76.7%
Masood et al. 2015	90%	88.3%
Andrėkutė et al. 2016	85.8%	79.6%
Odeh & Baareh 2016	96.7%	91.3%
Tan et al., 2016	83%	89%
Kostopoulos 2017	82.9%	96.5%
Ozkan & Koklu 2017	87.08%	94.86%
Dorj 2018	96.9%	94.17%
Gautam et al. 2018	70.38%	83.54%
Kharazmi et al. 2018	85.3%	94%
Saleem et al. 2019	93.27%	98.47%
Leon et al. 2020	87.5%	100%

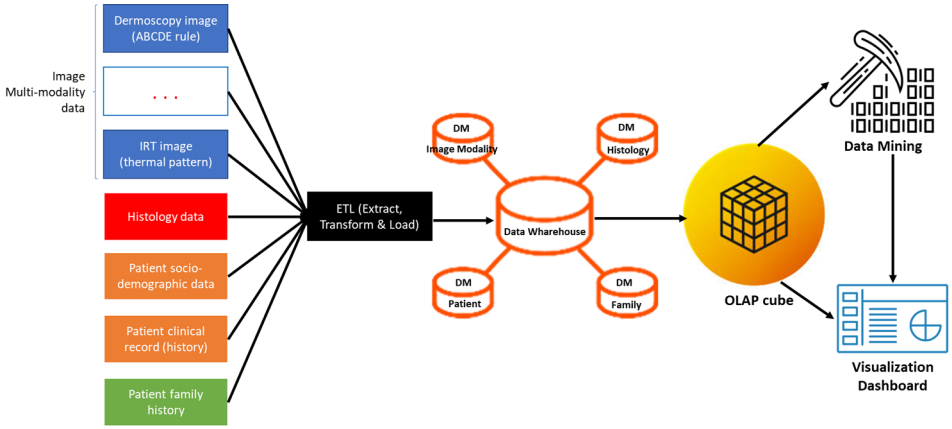
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PROPOSED IMPLEMENTATION

A Decision Support System (DSS) has three main components: Dataset, Inference Engine and User Interface and should have as main goal to support its users in aiding their decision making in a bias free and transparent manner (Sauter, 2014).

For an effective skin cancer DSS the data should be of multiple sources, as more and detailed data will provide better insights for the decision-making process and better characterization of the problem. Relying only on ABCDE dermoscopic rule has been exhaustively tested and has limited accuracy, as seen in the previous section. With new emerging imaging modalities presenting promising results, a multispectral based DSS is expected to perform better, although it also brings new challenges and complexity. This added with histology, patient clinical history (probably obtained for an existing Electronic Health Record), patient socio-demographic data and patient family history of skin conditions will provide full data to build information and knowledge to aid for better decisions. Based on this the proposed infrastructure showed in fig. 3 will have all the mentioned sources. Though, it is important to refer that not all the imaging modalities are available in the Digital Imaging and Communications in Medicine (DICOM) standard and stored in the Picture Archiving and Communication System (PACS), so proprietary data storage implementations must be considered. Each imaging modality (Dermoscopy, HFUS, CSLM, OCT, APB, MLSM, BEI, IRT, PDD and UV) will be a data source along the histology, patient health record, patient socio-demographic and patient family skin condition history datasets. The data will be processed by an Extract, Transform and Load (ETL) system to correct data ambiguity, discrepancies, and outliers. Additionally, it will be stored into an offline Datawarehouse (DW), being divided in different tables, i.e. Datamarts (DM) and correspond to the original multiple source data that are linked through a fact table (fig. 4), which facilitates the data selection for the Data Mining tools and Visualization at the Dashboard.

Figure 3. The proposed skin cancer Decision Support System general infrastructure.



The data can be presented in several forms. It can be a raw image, a processed image (e.g. segmented, histogram analysis, region of interest analysis, cross-section analysis), text, numeric, binary, date type or categorical.

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In the Data Mining tools several operations may be applied to the data, which can be supervised or unsupervised learning algorithms. For some datamining operations binarization or normalization of an attribute might be required.

With the unsupervised learning methods. Clustering and Data Association can be practiced. The clustering can be performed through KMeans or Hierarchical clustering, this helps to establish groups among selected data. The association is normally based in rules of different attributes association to identify patterns and normally employs the Apriori algorithm (Witten et al., 2016).

The supervised learning approach is based in prediction/regression methods and classification. The prediction/regression methods use the input data to through a linear (all numeric data) or logistic (numeric and categorical data) formula, estimate a new output. This can be achieved using linear regression methods, which can be simple or multivalued or a logistic regression. For classification, there are several methods available to be employed, all based in diving the dataset in two groups: the training set and the testing set. Commonly, a division of 70/30% is selected, although other configurations can also be applied. The training will be used to train the model built with the selected algorithm, and respective parameters adjusted. The accuracy value obtained will represent the probability of a given new record of the dataset to be correctly classified. Among the most common classification methods there are: MLP, also known as ANN, SVM, NB networks, DT, Random Trees, RF, kNN, GA, Fuzzy Logic, Logistic Regression and the AdaBoost (Witten et al., 2016). Based in the previous section the already used in a single modality classification, that proved its utility, are ANN, SVM and NB.

Once the data is stored in a clean and correct form in the DW and DM, through the OLAP cube, it will be possible to perform different views and queries on the related data. The fact table (fig. 4) is indispensable in this task, as it maintains the correspondence between the related data. With the OLAP cube it is possible to perform the operations Roll-up (reducing dimension through aggregation), Drill-down (fragment data into small parts, increasing a dimension), Slice (selecting one dimension of data), Dice (selecting only two or more dimension, but smaller than the original cube) and Pivot (rotates the data axes to provide a substitute presentation of data) (Sauter, 2014).

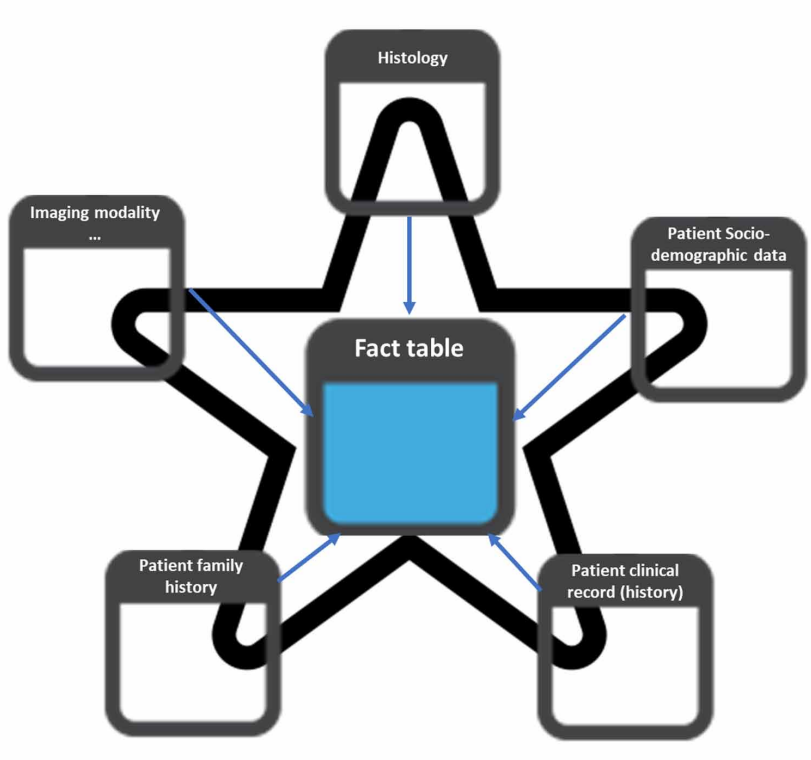
It is important to mention that, despite the main goal of a skin cancer DSS being focused the production of a prognosis for a patient examination, it should also support that indication with more data representation and visualization tools, such as charts. This is important because, at the end, the responsibility of the diagnosis is entirely of the physician and not of the system, as it only gives him a hint.

The produced dashboard should be operational, reflecting the actual state of the patient lesion and its relationship with history. It must enforce simplicity, readability, and focus. The dashboard should use different shades of the same color, avoid using any logo, avoid using data navigation, use 2D graphics instead of 3D graphics, use lines and borders sparingly, use rounded metrics and simplified details, use the same font, color palette and style, use some space between the elements, avoid multiple views, scale sections according to the same space and group data logically.

In terms of charts at the dashboard, they depend in the objective of showing them. For comparison between items: if there are two variables per item, it should be used the variable with column chart; if there is only one variable per item, but many categories, it should be used the table with embedded charts; with few categories, but many items, it should be a bar chart; for few items, a column chart. For overtime comparison: if there are many periods and cyclic data should be a circular area chart, or non-cyclic data a line chart; if there are few periods and single of few categories, a column chart is recommended or with many categories, a line chart. For data distribution: if there is a single variable and few data points it is recommended a column histogram, or many data point a line histogram; if is two variables, a scatter

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Figure 4. The representation of the Datawarehouse fact table and its relationship in star with the Data-Mart tables in the support to the OLAP cube.



plot should be used, and for three variables a 3D area chart. For data composition: if static and a simple share of total, it should be used a pie chart; if accumulation or subtraction of total, a waterfall chart; with changes over time if there are few periods, a stocked column chart is recommended, if there are many periods, a stocked area chart. Finally, for relationship between data: if there are only two variables, it should be used a scatter plot, if three or more a bubble plot is recommended.

This proposal for DSS is generic, as it always depends on the question that the system must give a response. Still, the proposed infrastructure, if well parameterized, can respond to more than a single question. For a more intelligent dashboard, some interactivity can be implemented, presupposing, per example, a pressing of a chart or text to show more related detail to it.

DISCUSSION AND CONCLUSION

There is no doubt of the valued contribution of DSS to aid health professionals with the growing rise of skin cancer and shortage of specialists. Most of the developed solutions, which are mainly research oriented and institution self-solutions are based in a single modality of diagnosis. Only one implementation was multicenter (Kostopoulos, 2017), but based in the simple dermoscopic image ABCDE rule. The majority of the skin cancer DSS implemented to date focus on this rule, which is also the common practice in daily clinical setting. Although for better discrimination, on a confounding lesion, relying in

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this rule is not enough and selecting a histology lab test is costly and dilatory. This leds to the emergence of promising imaging techniques, which are now becoming to be adopted. Still, some require validation against the histology gold standard, which, with the absence of a multi-source dataset freely available, is limited in terms of time and funds.

It is important to mention that a DSS to become useful, must surpass the performance of a specialist (Przystalski et al., 2010). The best reported results for the ABCDE rule DSS are using SVM (Baldi et al., 2009; Masood et al., 2014; Premaladha & Ravichandran, 2016; Dorj, 2018; Saleem, 2019), even when combined with another ML algorithm such as Adaboost (Przystalski et al., 2010). Other supervised ML algorithm that performed with an accuracy over 90% was the MLP or ANN (Dreiseitl et al., 2007; Kostopoulos, 2017; Ozkan & Koklu, 2017), a proposal result was achieved when combined with NB (Ruiz et al., 2008). On other imaging modalities, the best achieved accuracy was obtained for a spectrophotometric DSS using ANN (Carrara et al., 2007), followed by the fluorescence images using kNN (Odeh & Baareh, 2016), MSLS using NB (Li et al., 2014), hyperspectral imaging with SVM (Leon et al., 2020) and ultrasound images with SVM (Andrėkutė et al., 2016).

The proposed DSS implementation is generic and conceptual, being out of scope of this publication to constrain it to a specific technology or development environment, as it can be implemented on most of the current available development and storage tools. From this research, it is clear that with the existing freely available datasets on skin cancer, an effective DSS for skin conditions using a multi-imaging approach it cannot be implemented. The majority of the existing DSS only addressed a specific and simple question, but future practice may demand more information, in specific for the differential diagnosis. The proposed open architecture is dynamic in allowing multiple questions, which through OLAP and data mining is possible to add and adjust questions. In a multi-modality data source approach, different data mining and visualization tools can be used for different modalities, making the proposed system flexible. To the authors knowledge, there is no implementation of this kind for dealing with skin cancer, being the proposed more comprehensive and could cope with other dermatological conditions. This is the first step towards a technological need. It is important to enforce the idea to health professionals that it is easier to engage with new advanced computational tools than being afraid of losing a job to a smart system, showing resistance to their adoption, becoming these technologies a facilitator in their practice.

At this publication, the current diagnosis and treatment options for skin cancer, the existing promising imaging technologies to improve it and the existing free datasets for research were presented, the application of DSS in skin cancer were reviewed and a generic technologically advanced effective DSS for skin conditions management was described.

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KEY TERMS AND DEFINITIONS

Accuracy: Parameter that represents the number of individuals correctly diagnosed among a given group, by a clinician or decision support system.

Basal Cells: Epidermis skin cells responsible for producing new skin cells.

Business Intelligence: Software tools that can analyze large data quantities and retrieve information to reach knowledgeable conclusions.

Computer-Aided Diagnosis: System that supports medical diagnosis and helps in treatment selection.

Data Mining: Process involved on the harvesting of information from unprocessed data.

Datamart: Subset of a data warehouse focused on a specific topic of information, per example, patient information.

Datawarehouse: Electronic system for the collection and manipulation of large amounts of data.

Decision Support System: Computational system employed to assist, sustain decisions, and select the best course of action.

Deep Learning: Subfield of machine learning that mimics the workings of the human brain in process of data analysis, interpretation and decision making.

Dysplasia: Abnormal cell development, normally associated to the appearance of pre-cancerous or cancerous lesions.

Echogenicity: The capability of a given tissue to bounce an echo. This ability is low for hypoechoic structures (denser) and high for hyperechoic structures.

Expert Systems: Computational system build to mimic the capability of a human specialist to perform a decision.

Fluorophores: Fluorescence compound that can radiate light upon excitation with a light source.

Inference Engine: Section of a machine learning system destined to logically interpret a given data set and retrieve information from it.

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Keratinocytes: Epidermis skin cells that originate from the differentiation of basal cells, composing approximately 85% of epidermis. It is the skin constituent responsible for the synthesis of vitamin D and keratin production.

Langerhans Cells: Epidermis skin cells with immunological functions.

Machine Learning: Scientific area of Artificial Intelligence focused on the development of algorithms and/or systems with the ability to learn, modify in an automatic manner and reach decisions, based on data patterns.

Melanocytes: Epidermis skin cells that produce and store melanin, a pigment that absorbs ultraviolet rays, blocking its nefarious actions.

Merkel Cells: Epidermis skin cells that play a role in human sensing and work as mechanoreceptors.

Metastization: The ability of malignant cells to infiltrate neighbor tissues and close-by vascular and lymphatic structures to spread to distant organs.

Neoplasm: Atypical growth and agglomeration of cells.

OLAP Cube: Array with large amounts of data used for multidimensional analysis.

Sensitivity: Measure of the ability of a clinician or decision support system to correctly identify those who have the disease.

Specificity: Measure of the ability of a clinician or decision support system to correctly identify those who do not have the disease.

Supervised Learning: A machine learning algorithm that learns from labeled data included in a training set.

Unsupervised Learning: A machine learning algorithm that learns from unlabeled data, learning and detecting characteristic data patterns on its own.

User Interface: Platform created for the interaction of a human operator with a computer.

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APPENDIX

Acronyms

AK – Actinic Keratosis
ANN - Artificial Neural Network
APB – Adhesive Patch Biopsy
BCC – Basal Cell Carcinoma
BEI – Bio-Electrical Impedance
CBIR – Content-Based Image Retrieval
CSLM – Confocal Scanning Laser Microscopy
DICOM – Digital Imaging and Communications in Medicine
DT – Decision Trees
ECOC – Error-Correcting Output Coding
EHR – Electronical Health Record
ETL – Extract, Transform and Load
GA – Genetic Algorithms
HFUS – High Frequency Ultrasonography
IRT – Infrared Thermal
kNN – k-Nearest Neighbor
LDA – Linear Discriminant Analysis
MLP - Multilayer Perceptron
MPLSM – Multiphoton Laser Scanning Microscopy
NB – Naive Bayes
OCT – Optical Coherence Tomography
OLAP – Online Analytical Processing
PACS – Picture Archiving and Communication System
PDD – Photodynamic Diagnosis
RBG – Red Blue and Green
RF - Random Forest
RT – Random Trees
SCC – Squamous Cell Carcinoma
SSAE – Stacked Sparse Auto-Encoders
SVM - Support Vector Machines
UV - Ultraviolet

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Chapter 22
Web-Based Machine Learning Application for Heart Disease Prediction:
Machine Learning in the Healthcare Industry

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ABSTRACT

Risk because of heart disease is increasing throughout the world. According to the World Health Organization report, the number of deaths because of heart disease is drastically increasing as compared to other diseases. Multiple factors are responsible for causing heart-related issues. Many approaches were suggested for prediction of heart disease, but none of them were satisfactory in clinical terms. Heart disease therapies and operations available are so costly, and following treatment, heart disease is also costly. This chapter provides a comprehensive survey of existing machine learning algorithms and presents comparison in terms of accuracy, and the authors have found that the random forest classifier is the most accurate model; hence, they are using random forest for further processes. Deployment of machine learning model using web application was done with the help of flask, HTML, GitHub, and Heroku servers. Webpages take input attributes from the users and gives the output regarding the patient heart condition with accuracy of having coronary heart disease in the next 10 years.

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I. INTRODUCTION

Lots of people are dying due to Coronary heart disease (CHD). Coronary heart disease happens where your coronary arteries are, that delivers a constant blood supply to your heart these arteries that set on top of the heart because your heart in order for those that muscle to work properly it has to have constant fresh oxygenated blood going to it and in the arteries when it starts to develop the fatty plaques which causes blockages or restrict blood flow to the heart and these fatty plaques are caused by a condition called atherosclerosis and this occurs in the artery wall(Katarya & Srinivas, 2020).

This stops blood flow into certain parts of heart and cause to death. Smoking causes a lot of basic constriction and damages those arteries increases chances of plaques forming. Being obese or overweight, having a high cholesterol level having a sedentary lifestyle, Diabetes or Family history these all causes Heart Problems. In order to prevent Coronary heart disease in addition to medical therapy, the other cornerstone is lifestyle it's weight loss, stop smoking, attending to diet and exercise and the only one who can really think about that and do that is the patient themselves There isn't a cure for atherosclerosis so the patients can do something to slow down its progress and earlier you start, the better this for you (Golande & Kumar, n.d.).

Here comes the ML in action, we can predict the Heart Disease very early with the help of history and current condition of person and we can save that person from a heart attack or stroke. Machine Learning is taking revolutionary step in healthcare by enhancing the quality of automation. The increasing number of application of Machine Learning in healthcare allow us to glimpse at future based on the dataset, analysis which ultimately leads to help countless patient (Uddin et al., n.d.).

Various factors responsible for Heart disease are overweight Cholesterol, blood pressure, Diabetics, and habits such as Smoking, Consumption of alcohol. Early Symptoms of Heart attack includes Fatigue, Shortness of breath, Pain and discomfort in chest, Heart burn or abnormal pain, Rapid or irregular heartbeat, Pain may spread to left or right arm or to neck, jaw, back or stomach, Cold sweat and unsteadiness (Giripunje et al., 2021; Golande & Kumar, n.d.; Katarya & Srinivas, 2020; Uddin et al., n.d.).

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II. LITERATURE REVIEW

Table 1.

Sr. No.	Title of the paper(Year of Publication)	Methodology
1	Heart Disease prediction Using Machine Learning Algorithms(Singh & Kumar, 2020) (2020)	1. Data collection done using UCI repository dataset. 2. Used 37% testing dataset and 73% used as training dataset the system. 3. Selected 14 attributes for prediction system. 4. For pre-processing the dataset conversion of categorized value by dummy value has done using data balancing technique. 5. Testing and training of algorithms has done. 6. Calculated and compared accuracy of each algorithms with the help of confusion matrix 7. Concluded that the K-nearest neighbor with 87%accuracy was much efficient as compared to others.
2	Improving the Accuracy in Prediction of Heart Disease using Machine Learning Algorithms(Keerthi Samhitha & Sarika Priya, 2020) (2020)	1. Chose Cleveland heart dataset by UCI for pre-processing. 2. During pre-processing the dataset 6 records get expelled from dataset as they had null values. 3. Used Decision tree, KNN, K-mean grouping and Adaboost classifiers in order to get accurate classifier. 4. Concluded that the K nearest neighbor was the accurate.
3	Prediction of Cardiovascular Disease Using Machine Learning Algorithms with SDNKL(Sri et al., n.d.) (2020)	1. Data used for this project was from Hungarian, Switzerland, Cleveland and Long Beach VA database from UCI machine learning Repository. 2. After pre-processing the data, different Machine Learning algorithms were applied. 3. Accuracy for all used algorithms were calculated and compared.
4	Prediction of Heart Disease Using Machine Learning(Gavhane & Pandya, 2018)(2018)	1. Chose Cleveland dataset from UCI library for the process. 2. Selected attributes such as Age, Sex, Blood Pressure, Heart Rate, Diabetes and Hyper cholesterol. 3. Tested and trained Dataset using neural network algorithm multi-layer perceptron (MLP) machine learning algorithm.
5	Early Detection of Heart Syndrome Using Machine Learning Technique(Basha et al., 2019) (2019)	1. KNN algorithm is used as machine learning algorithm, 2. confusion matrix, is used as classification model

III. METHODOLOGY

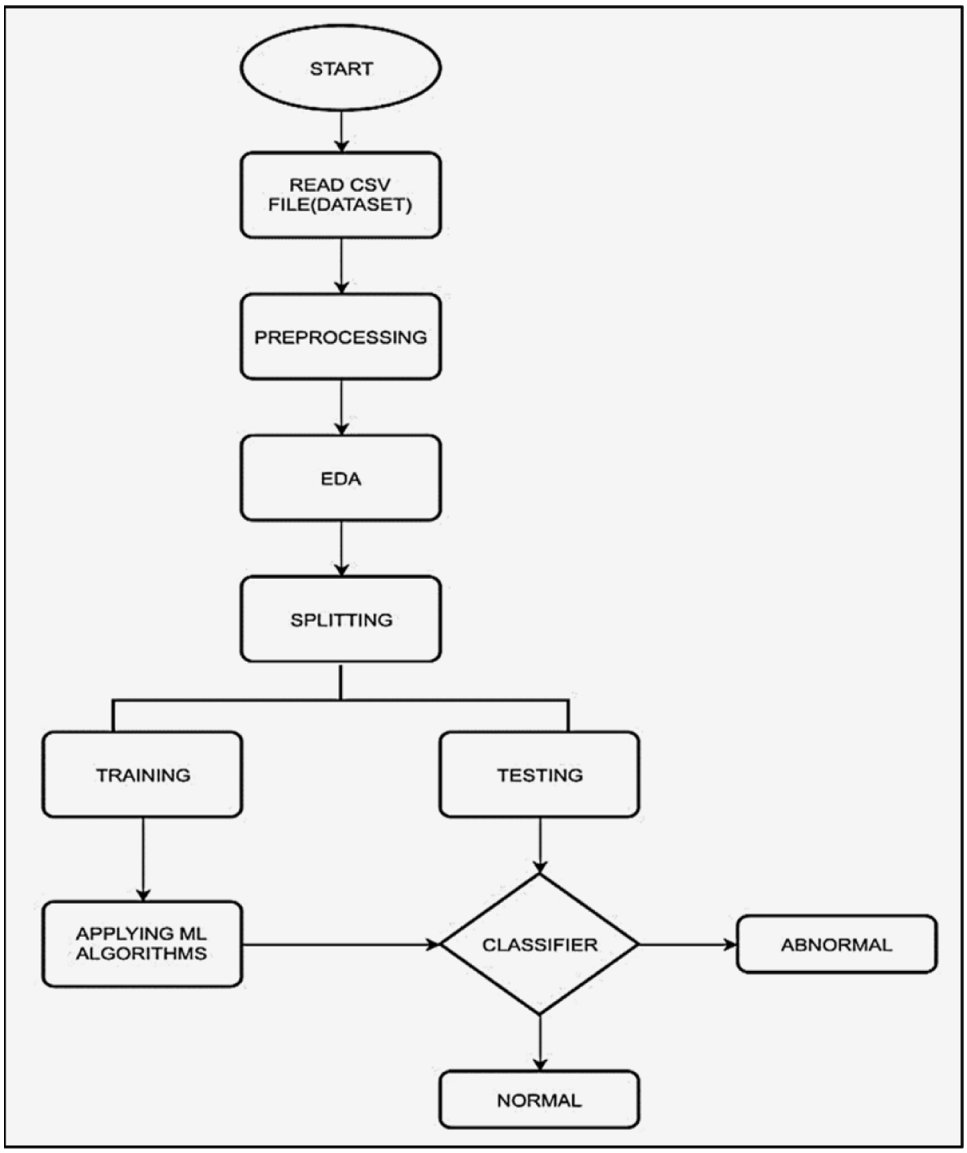
In this work, Heart disease Prediction is carried out using machine learning with the following steps

1. Dataset Collection.
2. Importing Necessary Libraries.
3. Data Preprocessing.
4. Resampling Imbalanced Dataset.
5. Feature Selection.
6. Model Selection.
7. Train the Model.
8. Test the Model.
9. Save the Model
10. Deployment of Model Using Flask.

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11. Version control system.
12. Create Web Application Using Heroku.

Figure 1. Workflow of the proposed system



IV. WORKING

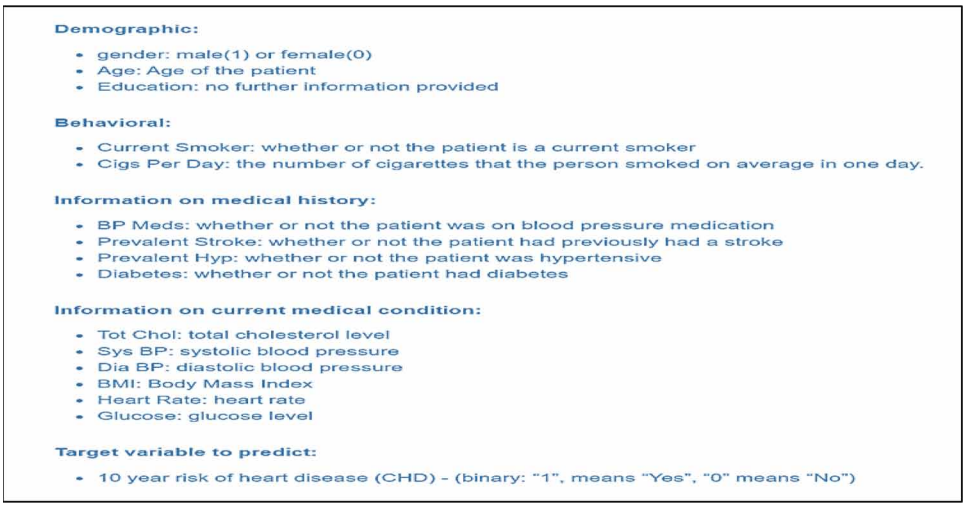
The goal of our work is to predict whether the person will have heart disease in upcoming ten years. Also, deployment of machine learning model by creating web application that allows user to quick guidance on basis of input parameters (Rajesh et al., 2018).

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A. Collection of Dataset.

- Dataset is collected from Kaggle.
- Framingham Heart Study dataset which contains about 4240 records and 15 attributes.

Figure 2. Attributes.



B. Importing Libraries

- Import necessary libraries which are required for the prediction like Pandas, Matplotlib, NumPy, Sklearn, Seaborn, Pickle etc.

C. Data Preprocessing

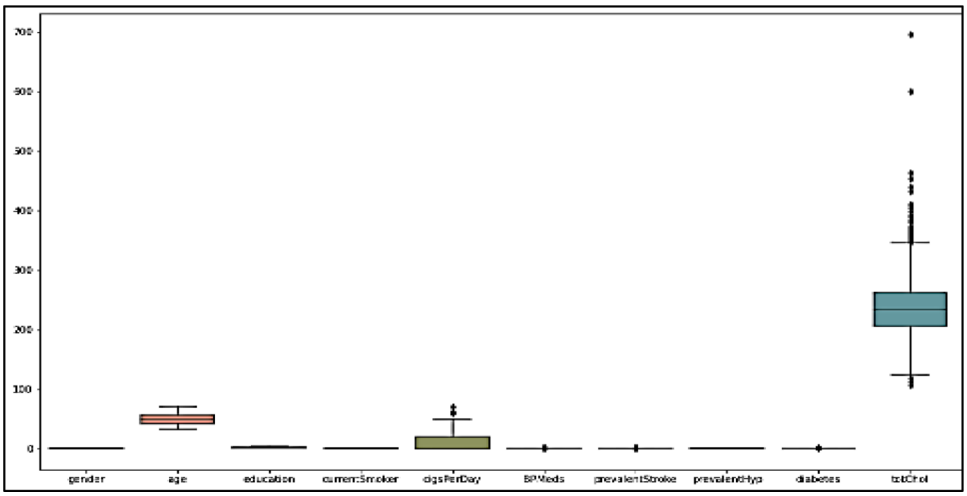
- Read the dataset using Pandas Library.
- Check if there is any null/ missing value present in dataset.
- There are several methods for removing null/missing value in dataset some of them are:
  - Replace null/missing values by the mean value.
  - Replace null/missing values by the median value.
  - Drop the records that contains null/missing value.
- Check for Outliers.
- If any attributes contain outliers then remove outliers using IOR(Inter Quartile Range) method.

D. Resampling Imbalanced Data

- Check for data distribution.
- If data distribution over no. of positive and no. of negative cases in a target attribute is not balanced or equal.
- Then using resample library from Sklearn we can equally distribute data.

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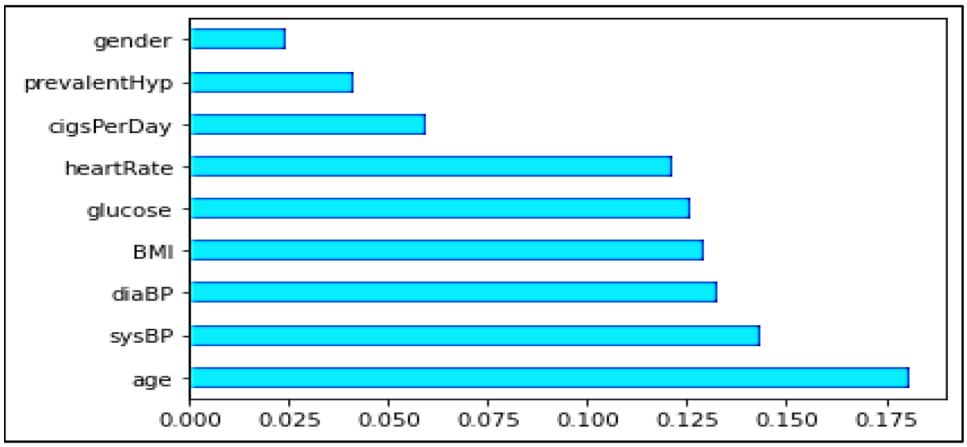
Figure 3. Boxplot to check Outliers.



E. Feature Selection

- As our dataset contains 15 attributes not all attributes are that much important for prediction.
- So, we can use ExtraTreesClassifier library from Sklearn to select important features.
- For this work we can take top 9 features for the prediction and that features are represented using horizontal histogram.

Figure 4. Top 9 important features.



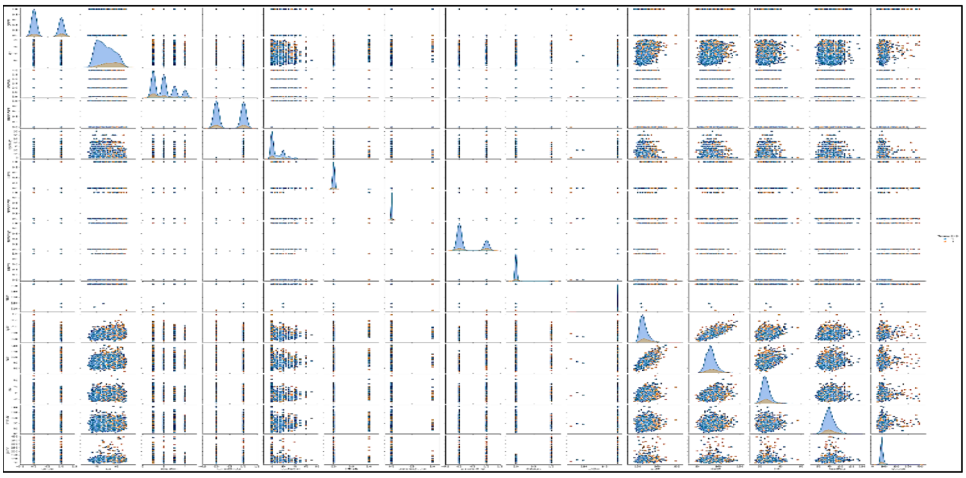
F. Model Selection

- Looking to problem we can say it is classification type.
- Also looking at pair plot we can say it is classification problem.

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- So, we can use k-Nearest Neighbors (KNN), decision trees (DT) and random forest (RF)
- For our work we use Random Forest algorithm.

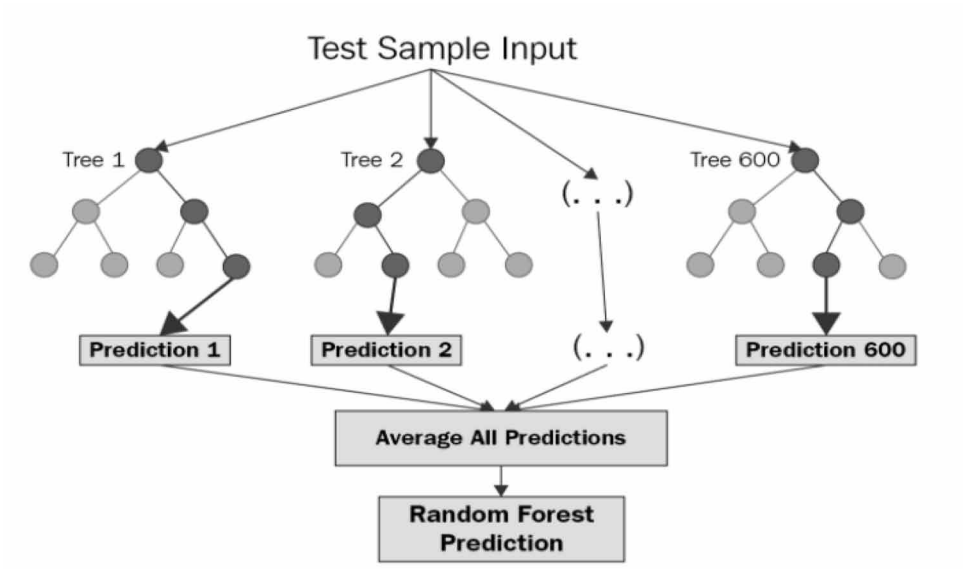
Figure 5. Pair Plot.



G. Train the Model

- The goal of training is to make a final prediction correctly as often as possible.
- Split data into the training and testing part
- Generally. 80% of data is took for train the model and 20% data is for the testing part.
- Form Sklearn we use train_test_split library for train the model.

Figure 6. Random Forest Regression Process



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H. Test the Model

- Test the model using trained data.
- Here are 2 examples of testing.
- Our model gives an accuracy of 97.22.
- Confusion matrix is given below.

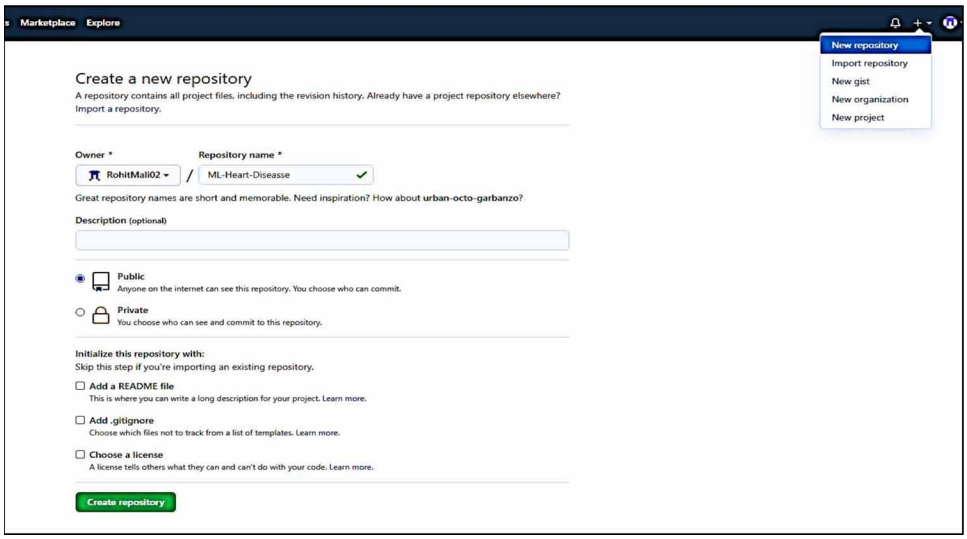
I. Save the ML Model

- We have created model using Jupyter notebook
- To save the model use pickle library.

J. Deployment of Model

- Create HTML file that contain nine input attributes.
- Create flask application.
- Import Flask object from flask library that create Flask application instance with the name app.
- @app.route() function in flask used for web requests.
- Also, Flask object provides render_template() function that manage HTML file to display 9 input attributes and output.

Figure 7. Create GitHub repository.

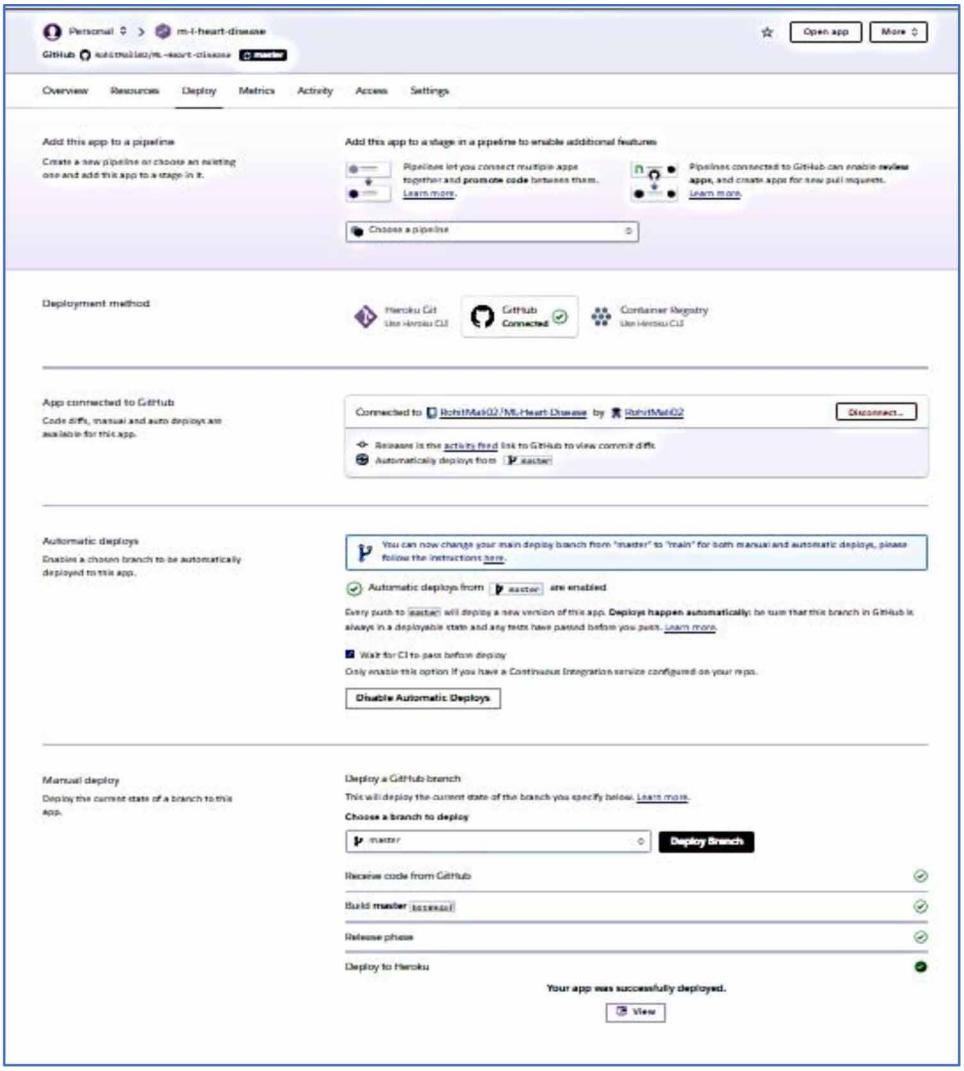


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K. Version Control System

- The version control is useful for if we have made any changes in our code so this system keep track of it.
- For this work we use GitHub as version control.
- First create free GitHub account and add new repository.
- Upload the required files from local repository to remote repository using git commands.

Figure 8. Heroku Cloud platform for model deployment



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L. Create Web Application Using Heroku

- Heroku is platform as service (PaaS) which is useful for operate and run your model in cloud.
- For deployment Heroku need some important file like runtime file which include a python version, requirement file which include the library used for prediction, procfile which is root directory of application.
- Create Heroku account → create new application → go to deploy section → connect to your GitHub account → Deploy branch.
- Above process will create a web application using flask and Heroku.

Model Link

https://m-l-heart-disease.herokuapp.com/

V. CONCLUSION

Considering the need to early prediction of heart disease, with this work we are providing real-time web application for heart disease prediction. This web based application takes various user attributes such as Gender, Age, Cigarettes per Day, Hypertensive, BMI, Heart Rate, Systolic Blood Pressure, Diastolic Blood Pressure, Glucose Level as input parameters and gives quick predictions depending upon inputs and previous data. Hence, we can predict the Coronary Heart Disease at early stage with the help of medical history and current condition of person and we can save that person from a heart attack or stroke. The use of Random Forest Regression Process yields better results as compared with other machine learning algorithms.

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Chapter 23
Web-Based Modernized Architecture Over Cloud Computing for Facial Extraction and Recognition

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ABSTRACT

Web content is diverse and is regarded as the primary source of accessible information that can be accessed through reference links. Web facial images are one type of web content that relates to important web pages and is considered important information for individuals. This chapter proposes face recognition as a service architecture that is based on real-world images from the web. The proposed service is implemented as a service for other third parties via cloud computing; additionally, its architecture is built via cloud using virtual machines that can be expanded based on resource demands. Web crawlers crawl web pages and retrieve images for elastic cloud storage. The collected images are then used to remove human faces and prepare the face images for identification and identifying the matched face of the set through successive phases. This chapter used PCA for features extraction and KNN for identification. Experiments show that increasing the number of crawler instances improves crawling speed and improves face recognition accuracy by preferring Euclidean over other metrics.

1. INTRODUCTION

In recent decades, the World Wide Web has emerged as the primary source of information; moreover, it is distinguished by a wide range of services. These resources are defined by URLs, which link to other resources. As a result, systems must monitor these URLs and their contents in order to index them and

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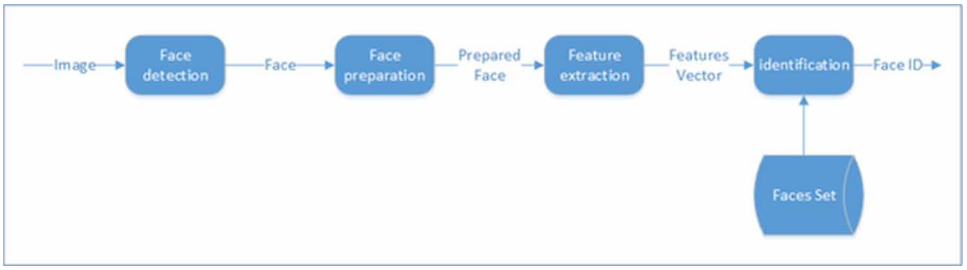
make them searchable. These are web crawling engines that are designed for fetching and collect web contents. The web crawling engines are designed for focusing on a particular form of content in the web pages.

The web page contents are also diverse, as they can be paragraphs, pictures, diagrams, or tabular content. Despite the fact that older engines were not based on the using of photos on web pages to search and instead focused on the paragraphs sections of every page (Rodriguez, 2014, pp. 1274-1285). As a consequence, search engines have recently introduced new capabilities that are based on this content, such as images based search engine. The photos' content might be for a number of items. As a result, image processing is used to look for photos on the internet (Jing, 2008, pp. 307-316). The image analysis methodology used varies depending on the picture categories.

Face recognition in the World Wide Web is a challenging task. As a result, there are numerous facial recognition algorithms require ordered set of training and provide varying planes of accuracy. Since web images are disorganized and unclassified, images downloaded from WWW must be arranged and classified. As a result, search for a humanoid facial on WWW necessitates two steps: the first is downloading pictures from WWW, and the next is enquiring the picture. Furthermore, since billions of pictures existed on the internet, facial recognition jobs require extendibility, precision, and rapidity (Ortiz, 2014, pp. 153-170).

Face recognition is a visual recognition problem that consists of four main modules as shown in fig 1; face detection, preparation, feature extraction, and identification. Face detection is responsible of check if the input image contains any faces or not, then extract the faces if exist. The face preparation phase preprocesses the extracted faces by cropping and resizing to expose and focus on a proper image for the next phase. Feature extraction is responsible of representing the face image in a features list in vector manner that can be quantized and compared with other. The extracted features vector is passed to identification phase to elect the nearest and the most matched face from a set of prepared faces (ElAraby, 2021, pp. 11723–11738).

Figure 1. Face recognition modules



The PCA algorithm is regarded as one of the most common methods for face recognition that is built on data decrease. Eigen faces are a statistical method that denotes the faces as a linear pattern of weighted eigenvectors (Poon, 2011, pp. 245-259), (Bahurupi, 2012, pp. 91-94). The eigenvectors are derived from a training set's covariance matrix. Eigenvectors introduced a new face space in which images are depicted.

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In addition, PCA is a valid method for feature selection and can select the most important variables that have most variation. Moreover, it is useful to speed up the computation and to improve the accuracy of classification model by reducing the dimensionality of the data and when there is a high dimensionality with high correlated variable (Anter, 2015, pp. 89-94), (Anter, 2015, pp. 89-94).

On another hand, KNN is a data mining algorithm that is ranked among the top ten in the scientific research (Wu, 2008, pp. 1-37). It is an efficient classification methodology which its classification of objects is depending on their proximity to train the objects. Furthermore, an entity is ordered based on a vote cast by its neighbors (Anter, 2019, pp. 670-687), (Anter, 2018, pp. 113-129).

Feature selection (FS) is an important step in the face recognition model to select a subgroup of input characteristics from the full facial data-set. FS used for recognizing and eliminating unnecessary, unrelated and disused attribute from data that haven't contributed to the accuracy of an analytical model, or may in fact decrease the accuracy of the model. Moreover, FSenables machine learning (ML) algorithms to train faster. It minimizes the complication of a model, and it makes it easier to infer. It improves the precision of a model if the true subset is elected. There two types of feature selection filter approach (based on statistical methods such as Pearson Correlation, Chi-Squared, Fisher, etc.) and wrapper approach (based on ML techniques for instance Lasso, Recursive Feature Elimination, etc.) (Anter, 2020), (Anter, 2020), (Anter, 2020), (Anter, 2019), (Anter, 2019).

Cloud computation, as one of computational paradigms, has several advantages, such as enabling rapid, on demand, and appropriate over internet accessing of a group of computational capabilities. Furthermore, these computing tools are programmable, virtual systems and facilities, quickly provisioned, scalable, and physically dispersed (NIST). Moreover, cloud computing has fundamental characteristics for example scalability, flexibility, and elastic. Cloud architecture refers to components, sub-components, tires, and overall association (Bahrami, 2015). The primary aim of cloud computation is to provide the computational properties like software, applications, platforms, and business processes in form of a service to cloud consumers via the internet (Inzinger, 2014).

Cloud computational paradigm has a unique administration challenges, such as providing scalability and scalable on-demand services, as well as developing cloud combination architectures and technologies (Moreno, 2012). There are also problems of cloud interoperability, customization, affordability, and convergence in cloud computing migration. According to an IDC survey, 80.2 percent of people believe there is no interoperability requirements, 76.8 percent believe that is difficult for integrating with IT organizations, and 76 percent believe there is a lack of ability to customize (Gens, 2009). As a result, cloud computing should be flexible in specifying a range of resources to meet the needs of individual cloud customers. Typically, service versatility is introduced by a flexible architecture that allows vendors to build a service for a specific group of customers.

In the cloud, the three service layers are categorized to Infrastructure, Platform, and Software as a service (IaaS, PaaS, and SaaS), and these layers support a range of user requests. However, cloud users may have demands toa service that is not offered by the unusual suppliers. As a result, the cloud users can modify their requests to take advantage of the available resources. In case of searching in WWW, there is neither API nor service designed to the crawling, despite the fact that generic APIs services exist at regular suppliers, just like the others applications (ElAraby, 2018).

There has been a lot of research and investment in the cloud computation systems to discuss an extensive variety of topics further generalization. As a result, cloud infrastructure companies compete to deliver more services and simplify their offerings in order to draw more customers. As a result, personalized web search creation services are available, allowing companies to create their own search engine. As

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a result, the APIs allow the consumer of cloud for creating a custom crawling engine to collect unique subjects, or paragraphs (ElAraby, 2019). As a consequence, it can be supported in the form of software-as-a-service level or, more precisely, crawler-as-a-service.

Contributions of this chapter as the following:

- It is proposed crawling structural design designed to humanoid facial finding, and identification.
- This suggested framework is built on the Cloud infrastructure to take its advantages and capabilities.
- Using service orientation, the suggested design addresses the succeeding topics: dynamicity, customizing, scalability, and service integration.
- This suggested design is built on the PCA algorithm for the features mining and characteristics decreasing, as well as the using of KNN for classification.
- This chapter uses web page pictures as a validated data-set for our search strategy.

The below shows how this chapter is structured: A section on related works provides previous studies on web crawling and its design. The section Proposed Web Crawler Architecture describes the proposed architecture for cloud computing in greater detail. View the test bed, outcomes, and analysis in the experimental results and research section, accompanied by the findings and possible works section.

2. RELATED WORKS

Many years ago, considerable works have been spent in researches of the internet crawlers and their structural design. Gray (1993) formed the earliest crawling engine. Gray called this engine as "WWW Wanderer". As an automated Web crawler agent, that navigates WWW to collect sites. Heydon (1999) suggested a portable and extensible crawling engine, called "Mercator" project that is designed and implemented with the Java. He addressed its key constituents of that modular web crawler, making remarks on replacements and relations in his design, and explaining its explicit constituents used in that project. Mercator APIs ease a role of installing additional modules by wrapping the crawler's network protocols or individual text processors.

Boldi et al. (2004) suggested UbiCrawler, a modular distributed network crawler. Its key characteristics were completely spread fault tolerance, direct scaling, device individuality, mission devolution, and internet domain dividing. Paolo also managed his agents and hosts using identifier-seeded stable hashing. The experimental findings of UbiCrawler indicated a linear relationship between the number of crawler agents and the number of records. Mika et al. (2008) proposed a web semantic module as part of a cloud computing web crawler. Regardless, they did not have web crawler architecture. Hsieh et al. (2010) proposed, adopted, and tested a stretchable crawling model. Furthermore, he concentrated on its filter language development, as well as filter dividing and document using to increase the concept execution. Xu et al. (2014) introduced a user oriented crawling engine that fetches the social media contents on the web adaptively. In addition, he created a module of feedback to measure the effectiveness score of the fetched document for refining its crawling processes. Bahrami et al. (2015) suggested a web crawler that based on cloud. His structural design is attentive on the Map-Reduce algorithm over scattered proxies.

Literature on face picture reveals a number of methods for the topic of web facial image. Ortiz et al. (2014) proposed an algorithm called LASRC that stands for "Linearly Approximated Sparse Representation-based Classification". LASRC methodology is researching large-scale face recognition while

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still concentrating on practical the open universe circumstances. This system is checked over Facebook faces data-set which it reflects real world situations. Wang (2012) have suggested a method called "Unsupervised Label Refinement-ULR". As a result, this ULR technique uses machine learning approaches to optimize the labels of network facial images. Furthermore, this system stated the learn complexity in a convex optimizing form and generated optimizing procedures to resolve the extensive learning tasks.

Facial recognition technique is considered as some of the multifaceted biometric methods in the recognition field due to the limitations resulting from variations in the presence of face pictures (Oloyede, 2020). Different face recognition technologies have documented significant achievement in well-controlled surroundings. Nevertheless, these methods have a tendency to fail as an effect of the unstable construction of facial images as well as in real-life scenarios because they make portraits of the same person's face appear different (Zhang, 2016, pp. 720–727).

One of the main problems in the facial recognition systems is the lighting variations or illumination (Sariyanidi, 2015). There are multiple approached that are discussed in different researches to handle this issue. Liu et al. (2014), they proposed two techniques for eliminating both high and low light segments on a face picture, and improves facial features in the low-end section. The proposed techniques were built on resident histogram terms for preparation process portraits of faces impacted with diverse illumination circumstances. The notions overdue this method were to successfully eliminate small and great rate lighting segments existing on the facial picture, as well as improve facial features located within the low frequency. Plichoski et al. (2018), they presented a framework for facial recognition by help of bio-inspired optimizing techniques. This method executes numerous techniques for feature mining and preprocessing, and the optimizing technique was accountable of selecting the approaches to apply, in addition to adjusting their factors. They studied the presentation of double optimizing techniques, specifically PSO "particle swarming optimization" plus DE "differential evolution" with the aim of addressing the brightness compensation problem. They used "Yale Extended B"DB for classifying process.

Wang et al. (2017), they proposed technique that based on adaptive weight "ULBP_MPHOG" and "WSRC" methodology using "Convolutional Neural Network - CNN". Initially, the facial pictures are standardized where the local unified binary form in addition to many histogram of the vector features were mined in every chunk. Information universe was an additional utilized to accomplish "ULBP_MHOG" structures. Test with CNN was performed on "CMU PIE", "Yale", "Extended Yale", and "ORL" data-set depending on the variable amount of chunks, feature types, and diverse classification techniques.

There are many facial recognition techniques that are proposed by many researchers. One of these techniques is the feature extraction techniques, which it reduces the original facial data-set through having set of characteristics which it is utilized to categorize, and obtaining the presented patterns through the input facial pictures (Oloyede, 2020). "Linear discriminant analysis – LDA" is denoted as "Fisher discriminant analysis". "LDA" is considered as one of widely utilized technologies in field of facial recognition. Not like "PCA" which it shapes a sub-space for facial representation, LDA builds subspace to distinguish between faces of different people (Chihaoui, 2016).

CNN (Convolutional neural network) is one of the used techniques in facial recognition, which it is seen to be stimulated by natural indication initiated in visual shell of mammal's mind. In visual shell, there are small areas of cells which they are subtle to specific areas of the visual ground. The test conducted via Wisel and Hubel also showed some specific neurons in the mind turn on once announcing edges of a definite direction. Some neurons lead to perpendicular boundaries although others lead to oblique or flat boundaries, in which neurons are put collected to carry out visual insight (Zhang, 2016).

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Abdullah et al. (2017), they proposed a facial identification approach that is based on two methodologies of feature extraction and classification. For feature extraction, they proposed AAM (Active Appearance Model) however it has faintness in its fitting. Also, they used ABC (Artificial Bee Colony) for convenient solution due to its ability to search quickly. Nevertheless, it has a weakness to searching in the neighborhood. They used the PSO-SVM, though; it undercuts its performance by using random values to calculate velocity. They proposed "Maximum Resource Neighborhood Search –MRNS" that is an improved "ABC" Algorithm to enhance the fit phase in "AAM". An adaptive "PSO-SVM" classification technique "AAPSO-SVM", in which the acceleration parameter values are selected using the atom suitability standards, is proposed to find the ideal constraints for the "SVM".

3. PROPOSED SYSTEM

This chapter suggests a facial recognition service architecture focused on the images that fetched by a crawler. Furthermore, this design is built on Amazon Web Service (AWS) to take advantage of the cloud computing features described in the introduction. Typically, recognition practices are executed to the datasets of ready pictures gathered from the site during the crawling step. As a result, WWW pictures are set in conjunction with the identification algorithm in order of readiness for the search practice. Following illustrates the five phases of the planned service architecture.

Figure 2 describes the first phase of crawling process for images, as described in Algorithm 1, in which the crawling of pictures is started with identifying kernel links, then storing them in the Frontier of URL. As a result, this service user moves the kernel links, which might be refer to individual pages, news sites, or wide-ranging sites for unspecified fetching. Crawl engine then retrieved the pictures from these got pages then saved them in the pictures storehouse. As a consequence, Figure 3 shows the crawling engine structure design which it is designed for running on cloud environment, and several VMs of crawl engines are created, that each engine operates independently. In spite of the Frontier of URL and images' storage are consolidated, all crawling engine VMs are synchronized.

Algorithm 1. Crawling and Extracting Images

Input: S: Seed URLs
Outputs: I: Extracted images
Steps:
// Step 1: Crawl the web pages andextract images
Set Frontier: S = { $u_1, u_2, ..., u_m$ }
Set Images Set: I = Ø
While length(S) ¹ 0**do**
u_i = Next(S)
P = Fetch(u_i)
I = I Èextract_images(P)
End Loop

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Figure 2. Images Crawling Phase

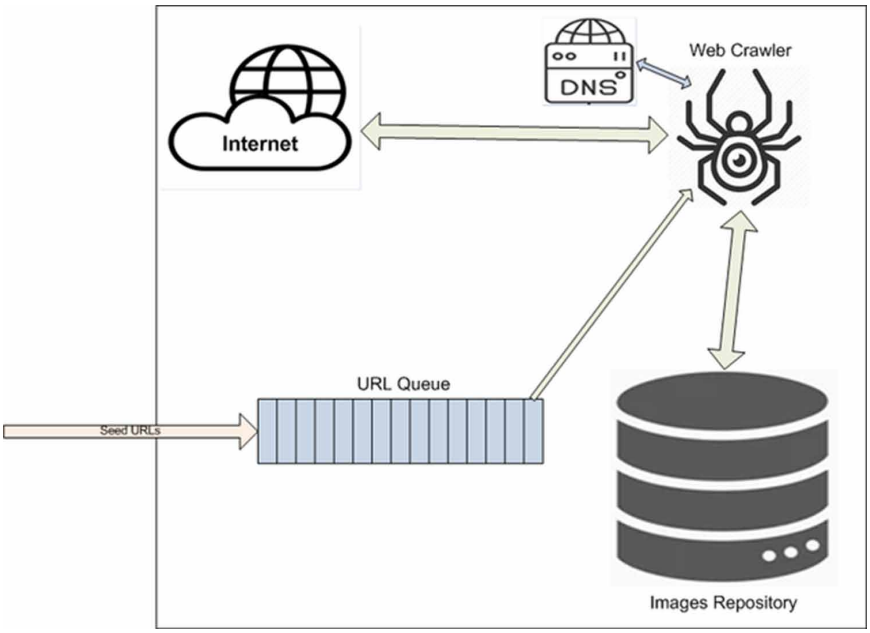
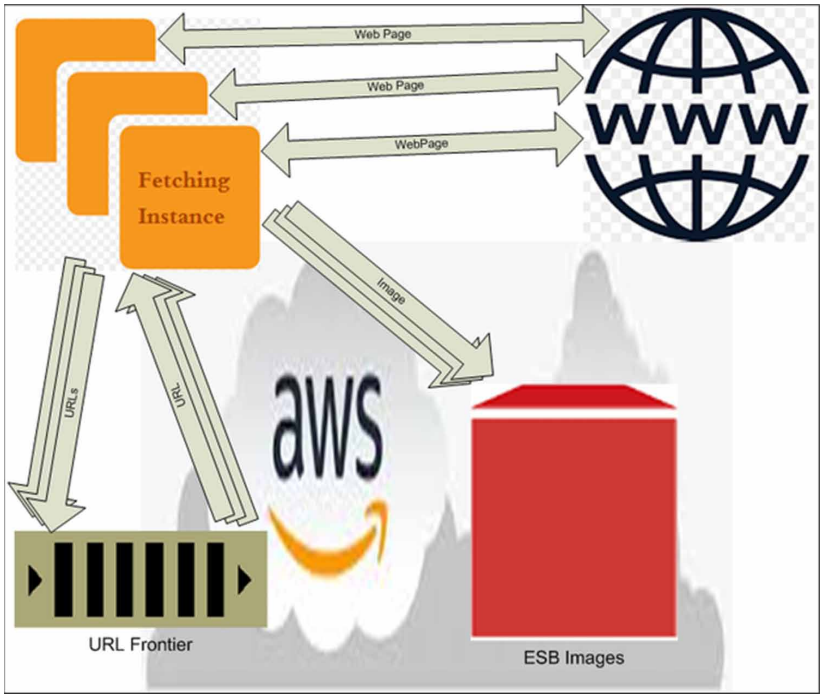
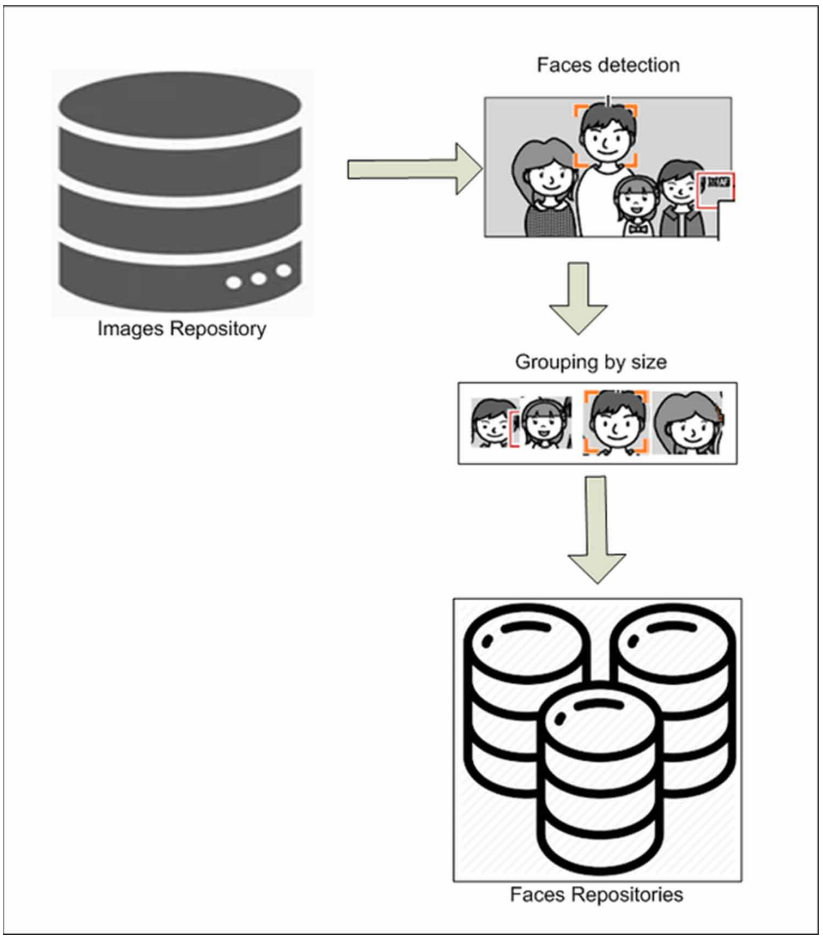


Figure 3.Crawling instances in cloud computing platform



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Figure 4. Face detection Phase



The second phase is face detection as in Figure 4, the fetched pictures are indexed, and the humanoid facial contained in the fetched pictures are extracted then stored in the facial repository. Furthermore, extracted facial are divided into classes based on their proportions. As a result, these classes consist of pictures with height and width values of 50, 100… 300. As a result, every mined facial frame is prepared by resizing to the closest category of predefined size class and saved in the community. Algorithm 2 clarifies the steps of crawling phase's 1 and 2 as well as face recognition, with a complexity of O (n log (n)).

Algorithm 2. Extracting Faces

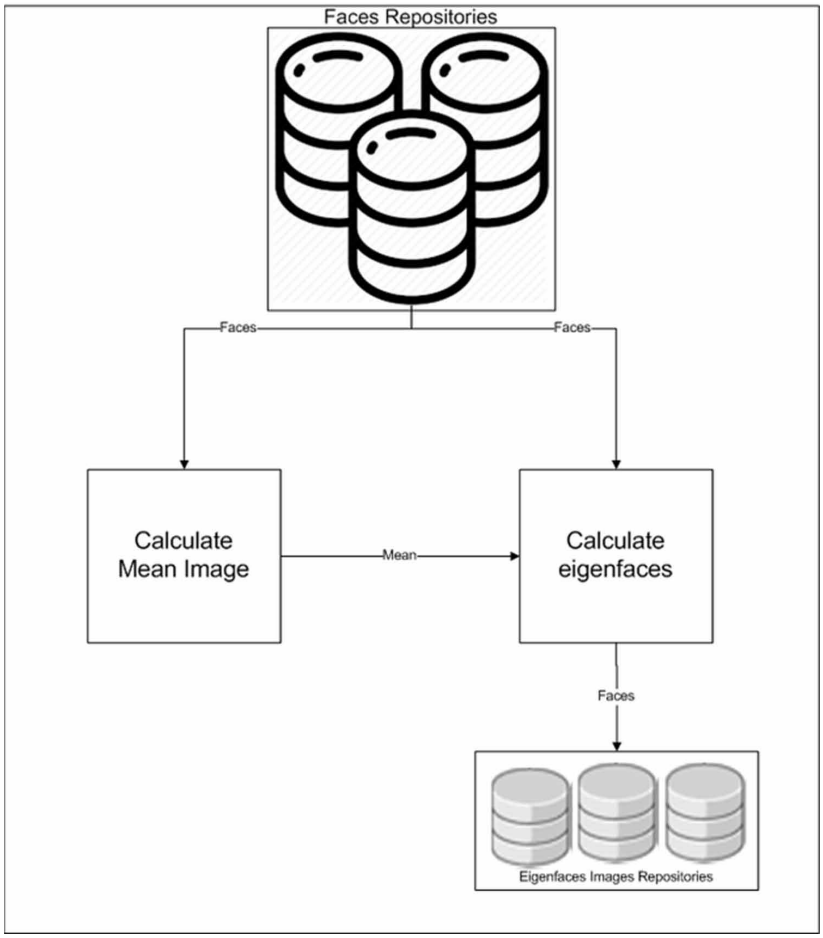
Input: I: Extracted images
Outputs: FR: Extracted Faces
Steps:
// Step 2: Extract faces and grouping
Set Faces group: FG = Ø
Set Faces Repository: FR = { FG_1, FG_2, FG_n }
WhileIhas next

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```
do
   IFS = Extract_Faces (I_i)
For each Face Img_j in IFS do
i = Determine_Nearest_Group(Face Img_j)
      FR = Insert(Face Img_j, FR, i)
   End For
End Loop
```

The third phase is face preparation as in Figure 5, which the first step in Principle Component Analysis (PCA) is considered to compute the mean matrix of the picture existed in the dataset of every segment, followed by computing the eigen-face for all facial picture utilizing the mean matrix and keeping it in the repository of eigen-faces.

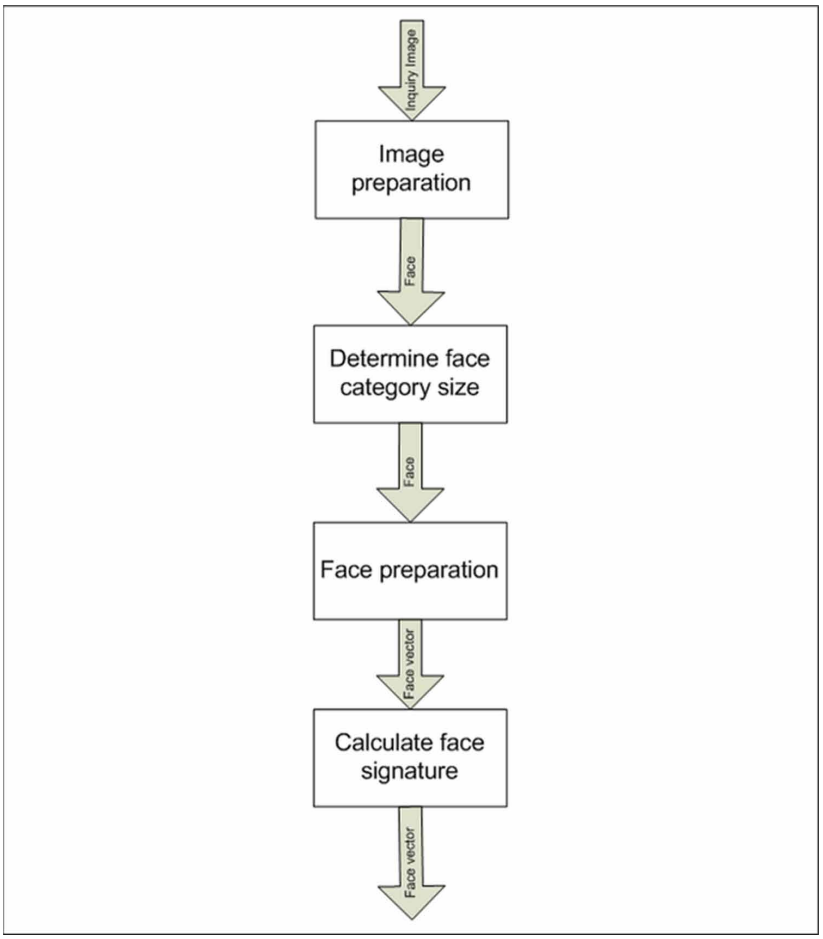
Figure 5. Faces preparation



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The fourth phase for the query image preparation as shown in figure 6, which the input for inquiry picture is handed as an input parameter for the proposed service; thus, the inquiry picture is preprocessed by identifying and extract the facial, deciding the best fit size class, and then change its size to this best size class; in this step, the signature of the inquiry facial is determined by the proper class mean. As a result, it is estimated on the Eigen-faces repository subset and the estimated data is assessed. Furthermore, the predicted list of size (K) is generated in order of holding (K) nearest neighbors of inquiry facial by a distance measurement.

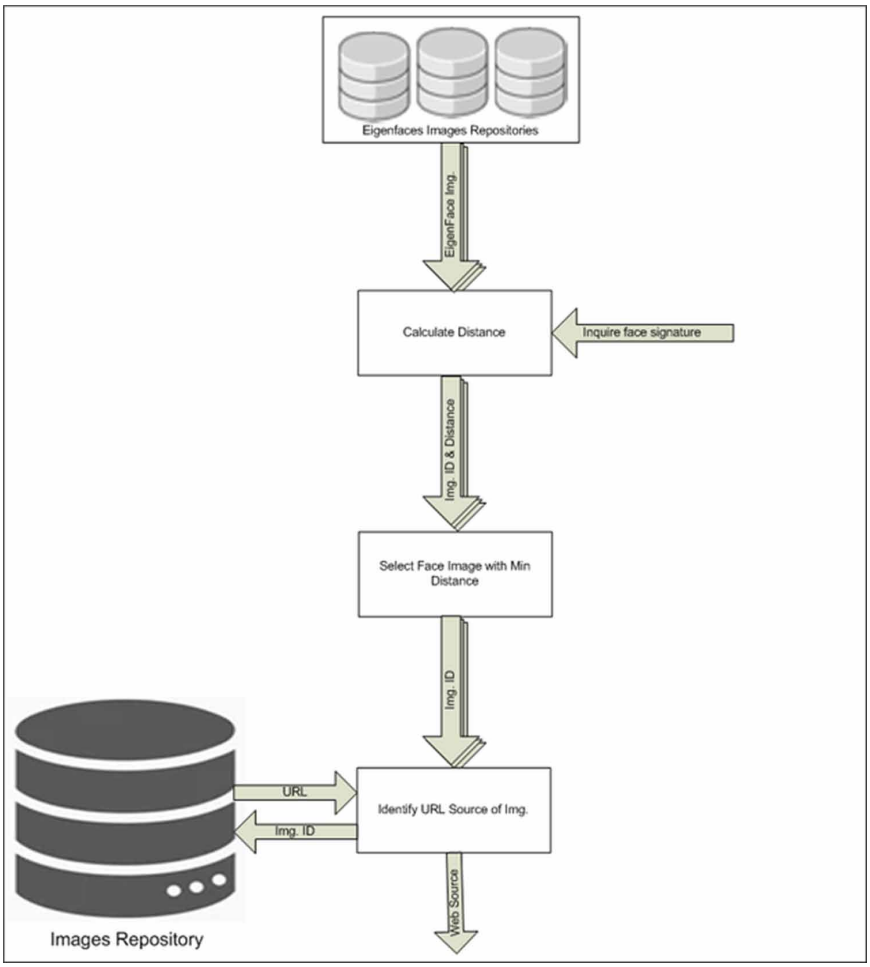
Figure 6. Query image preparation



The fifth phase is the distance calculation as in Figure 7. It calculates the distances between the inquiry picture and the facial pictures in the repository of Eigen-faces, after that choose smallest variance which it is representing the space between the inquiry picture and closest facial picture in the data-set, retrieve the URL of the crawled page containing the inquiry facial, and response to service consumer.

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Figure 7. Distance Calculation to Identify Web Source Face



The measures for measuring Eigen faces to crawl the facial pictures are represented in the right side in figure 8. The estimation processes began with getting the facial pictures of every size group, translating the pictures to a matrix (X(rc)) of values of picture pixels, and finally calculating their results, converting the matrix to a vector ($v_{rc\times 1}$), then calculating their mean vector ($M_{rc\times 1}$) of all pictures (n) in the group as in equation number 1, computing the covariance matrix (C) as in equation number 2, calculating the Eigen-vectors ($E_{rc\times 1}$) and the Eigen-values (λ) as in equation number 3, selecting the Eigen-values and choice the eigen-vectors matching to the largest 20 Eigen-values (V), and finally, calculating signature ($S_{n\times 20}$) of every facial picture in the dataset as in equations (4 & 5).

$$M = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{1}$$

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$$C = \frac{1}{n}\sum_{i=1}^{n}\left(v_i - M\right)\left(v_i - M\right)^T \tag{2}$$

$$CE_i = \lambda_{iEi} \tag{3}$$

$$vm = v_i - M \tag{4}$$

$$S_{n\times 20} = vm^{'} \times V \tag{5}$$

The measures for computing Eigen-faces of inquiry facial picture are depicted in the left part in Figure 8. The input picture is transformed into matrix ($Y_{\mathrm{r\times c}}$) as a consequence of changing it size to the appropriatedimensioned class, transformedthe matrix to vector ($R_{\mathrm{rc\times 1}}$), subtracted the mean ($M_{\mathrm{rc\times 1}}$) from inquiry vector to get ($P_{\mathrm{rc\times 1}}$) as in equation number 6, then catch the single of ($P_{\mathrm{rc\times 1}}$) vector (P'), after that computing the signature of theinquiry vector ($s_{\mathrm{1\times 20}}$) as in equation number 7. As a result, the signatures of facial pictures data-set ($S_{n\times 20}$) and the signature of the inquiry facial picture ($s_{\mathrm{1\times 20}}$) become ready to quantify the gap between them ($Z_{i\times 20}$) as in equation (8) where i=1:n and decide the face with the smallest distance in the data-set.

$$P = R - M \tag{6}$$

$$s_{\mathrm{1\times 20}} = P' \times V \tag{7}$$

$$Z_{i\times 20} = S_{i\times 20} - s_{\mathrm{1\times 20}} \tag{8}$$

4. RESULTS AND ANALYSIS

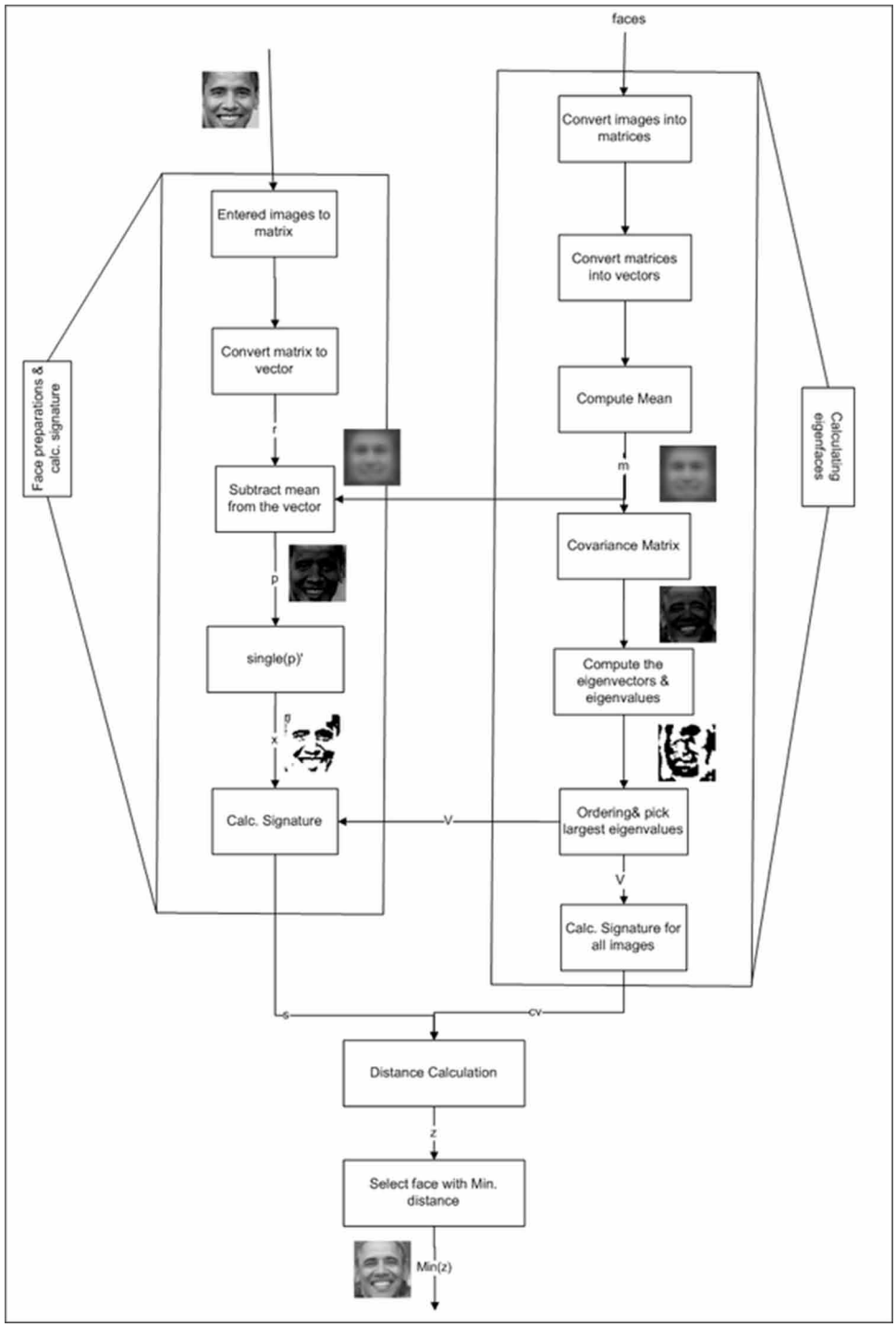
We performed trials to measure and investigate two related aspects: crawling efficiency and the accurateness of facial recognition procedures. The kernel URLs that are used in the crawl phase initiation was UCI Education site University of California (2020, Feb. 10) URL “https://uci.edu/”. As a result, the first experiment would compare the speed of picture crawling with many VMs versus a single crawling engine and a multithreaded crawling engine.

4.1. Multiple Crawling Engines on AWS Cloud

The first trial explores the efficiency of the theoretical crawling architecture in the cloud. As a result, efficiency is calculated by the time it takes to crawl the web pages and retrieve images using the extensions (.jpeg, .gif, .bmp, .tiff, or .png). As a consequence, running duration is calculated by seconds. As a result, we repeated the experiment five trials, each trial with a differ number of crawling instances: one, two, three, four, and five.

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Figure 8. Eigen-faces calculation



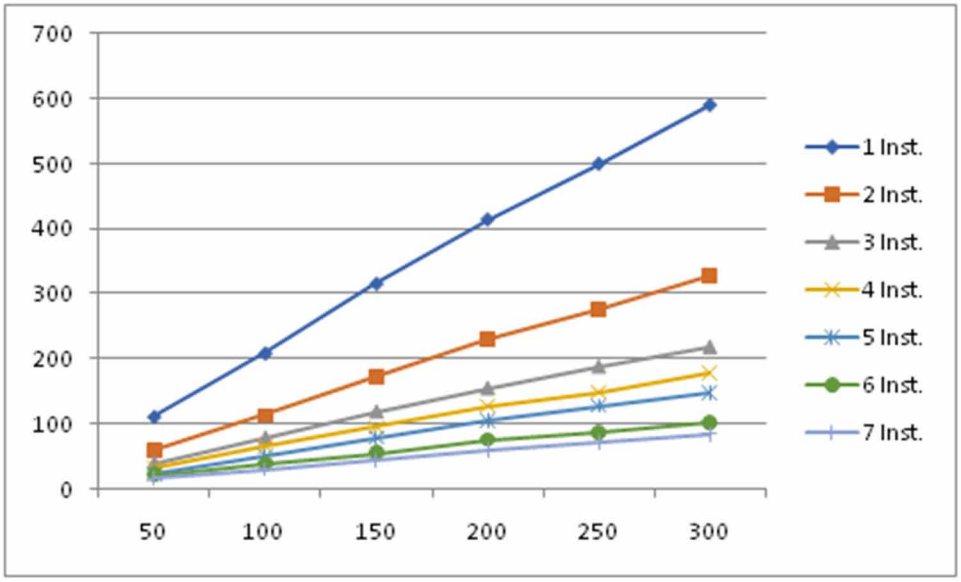
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This suggested system was designed and developed using OOP and open source programming tools and language such as LUNA eclipse as a development IDE, Java programming language and Java Development Kits version 8. The consolidated DB is structured to bring together the mined links from fetched documents; every minded link is related to an identifier key and an ensign to indicate the link status (handled or new).

The cloud experiments are executed on Amazon's Elastic Cloud Computing – AWS EC2, which every crawling instance runs on its own VM. Despite the fact that we instantiated from the "t2.micro" form, AWS EC2 offers a variety type of instance Amazon (2020, Feb. 15) AWS Amazon EC2 https://aws.amazon.com/ec2/ "t2.micro" is made-up of EBS Storage, memory1 GB, and Intel Xeon CPU3.3 GHz. Furthermore, network performance of "t2.micro" is varied from small to ordinary, and its speed ranged from 140 to 210 Mbps when the experiment was running. We set up the instances in the North Virginia (US East) Area. Furthermore, DB is designed on Amazon's Relational Database Service – AWS RDS, and it is configured to centralize for all crawler instances. RDS service is a relational DB that is usually scaled easily in the cloud computing environment, which this feature enables you to concentrate on the application and enterprise (2020, Feb. 15) AWS Amazon EC2. https://aws.amazon.com/ec2/. As a result, we used a MySQL DB instance of the "DB.t2.micro". Furthermore, "DB.t2.micro"is made-up of General Purpose DB Storage – SSD, a vCPU, and RAM 1 GB. The region corresponds to the same region and zone like as the crawling machines in Northern Virginia region (US East – Code: us-east-1).

The trial has two impacted coefficients; the first coefficient refers to the total of crawled pictures, and the other coefficient refers to the number of VMs. As a result, we repeated the experiment five times, increasing the number of instances from one to five. As a consequence, the figures of this trial are in Table 1 and Figure 9.

Figure 9. Performance of multiple virtual machines on AWS Cloud



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Table 1.Executing on multi-VMs on AWS

Number of Images No. of fetching instance	50	100	150	200	250	300
1 Inst.	111.02	209.94	314.57	413.12	498.98	591.05
2 Inst.	59.85	110.51	171.02	228.71	273. 87	326.96
3 Inst.	39.79	77.98	119.08	154.99	189.01	219.12
4 Inst.	31.49	64.95	94.97	128.57	149.91	180.09
5 Inst.	24.41	52.47	79.89	105.98	127.97	147.95
6 Inst.	21.47	39.12	56.31	76.59	87.98	103.98
7 Inst.	17.02	30.86	45.49	60.08	72.43	85.34

4.2. Performance of Facial Recognition

The second trial explores the feasibility of the suggested methodology depending on PCA in face recognition. As a result, we performed several experiments with multiple face photographs in order to identify them using datasets derived and obtained from WWW. The precision of facial recognition is checked multiply. As a result, a compilation of 20 facial pictures is entered, furthermore, it was resized to be included in one of these classes 50, 100, 150, 200, 250, and 300, and the identification of every picture was checked via its class data-set. Furthermore, various methods are used to assess the resemblance the enquired facial picture and the datasets facial pictures.

As a result, the Euclidean Distance is one of the suitable metrics that is used in a variety of implementations. It is usually the greatest crossable paradigm to different geometrical certainties of the facial scale field (Wang, 2013). It is proposed a methodology that depending on vector quantization of adaptive deep learning and the response of the system is measured by Euclidean (ElAraby, 2021). It is shaped of the summation of all squared distances between corresponding data points then takes the square root (sqrt) of this summation, as shown in equation (9).

$$d(p,q)=\sqrt{\sum_{i=1}^{n}(p_i-q)^2} \tag{9}$$

Moreover, the second one is the Manhattan Radius, also recognized as L1distance or the distance of city block (Borade, 2016). Absolute variances between couples of items are calculated using this technique, as seen in equation (10).

$$d(p,q)=\sum_{i=1}^{n}|p_i-q| \tag{10}$$

Furthermore, the Cosine Dissimilarity is the third one that computes the angle of a couple of vectors regardless their lengths (Zhang, 2003). Minimizing of angle between a couple of vectors refers to more alike. As a consequence, we use the inverse of equation 11 to create a distance measurement, as seen in equation 12.

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$$\cos\left(p,q\right)=\frac{p.q}{\left|p\right|\left|q\right|} \tag{11}$$

$$d(p,q) = 1 - \cos(p,q) \tag{12}$$

As seen in Table 2, we conducted our trials with varying figures of pictures and components, and all of the attempts correctly defined the right image from the dataset.

Table 2. Trials with a diversity of test facials and various number of PCA components.

Technique Test Trials	Euclidean	Manhattan	Cosine-Dissimilarity
Trial 1	12 – 13 - 14	14	14
Trial 2	10 – 12 – 13 - 14	10 – 12 – 13 - 14	10 - 13
Trial 3	3	3	10
Trial 4	3	3	10
Trial 5	10 – 11 – 12 – 13 - 14	13 - 14	10 - 12

As a result, the proposed identification strategy was tested using performance measures such as accuracy. We used various measures to assess the precision of the recognition procedure. Equation is used to measure the precision (13).

$$Accuracy=\frac{CT}{N} \tag{13}$$

Where *CT* denotes Correct Tries' number, and *N* denotes the tries' number performed by the measurement. As a consequence, the correctness outcomes seen in Table 3 and figure 10 are correct. We tried both metrics for the same amount of times. For both attempts, the Euclidean distance is used and adjusted the part number in the PCA extraction function. The same process is repeated twice using the Manhattan distance and the Cosine variation on both attempts.

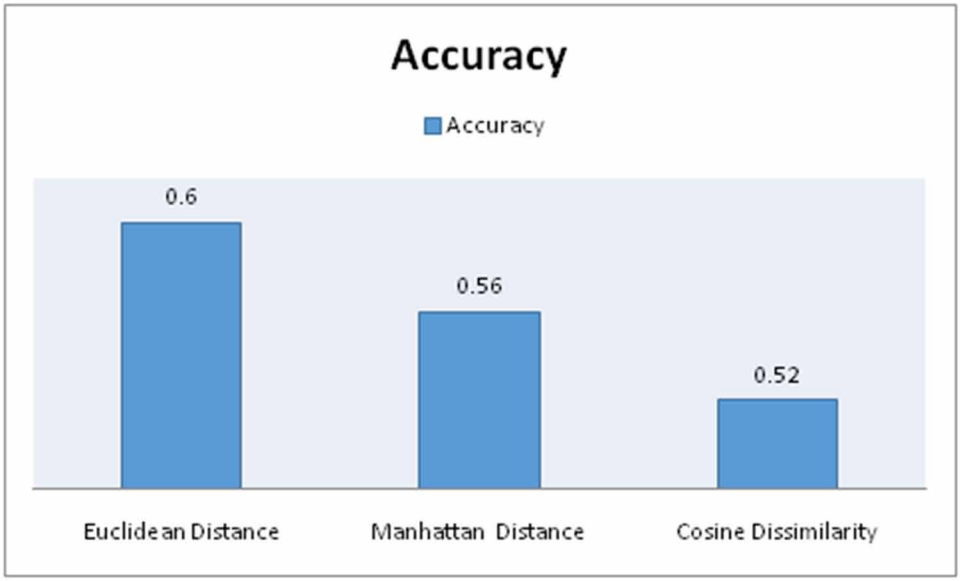
It is noticed from the consistency that the values are poor because of our data-set realism, where the facial pictures are observed and retrieved from live photographs rather than being composed in a straight line to be tested. Nevertheless, there is no redundancy in faces with the same person, which it is not the case in the other data-sets that are engaged and processed for trying and testing. As a consequence of both of these variables, the accuracies are poor. When we used the Euclidean, it achieved better values than using Manhattan or cosine dissimilarity.

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Table 3. Different metrics with the PCA accuracies

Cases	Euclidean	Manhattan	Cosine Dissimilarity
Accuracy	0.6	0.56	0.52

Figure 10. Different metrics with recognition accuracy



5. CONCLUSION AND FUTURE WORKS

This chapter suggested a facial recognition system presented as a service which it searches for the real-world pictures obtained through the web crawling. Furthermore, the system is built on the cloud, and it employs instant able VMs to accelerate the crawler's operations. As a result, the crawling stage is constructed as a series of separate and loosely coupled elements. As a result, design, scalability, and resiliency are also important considerations. As a result, the acknowledgment program will be offered as a web-based service to the other external systems. Furthermore, the recognition procedures use PCA procedure for attribute mining and KNN as a classifier with metric of distance. As a result, the following similarity measurements are employed: Cosine dissimilarity, Euclidean, and Manhattan. As a result, the trials findings reveal that increasing the simulated instances speeds up crawling and increases precision in face recognition using the Euclidean better than the other alternatives. For future direction, we plan to study and recommend a range of resources that can be delivered through the cloud computing, as well as a further adjustable crawling engine for a particular topic, focused on web content.

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