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Leveraging AI Technologies for Preventing and Detecting Sudden Cardiac Arrest and Death

Pradeep Nijalingappa, Sandeep Kautish, Mangesh M Ghonge, and Renjith V. Ravi

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Detailed Table of Contents

AI is used for alerting people who are suffering from heart problems. The patient's language, sound, accent, voice, and other patterns are analyzed in an audio call for heart problems. The CPR and defibrillation treatment is used. Delay in sudden cardiac arrest can create problems in the brain, and fatal implications might be there. Biosensors are recommended for heart patients, and they can be worn on the wrist to detect hypertrophic cardiomyopathy. This condition or disease occurs because of cardiac muscle thickening. This is the reason for heart failure, stroke, and fatality in heart patients. The other observation is outflow tract obstruction in the heart patients who had sudden cardiac deaths. This happens in patients who have high blood pressure and can be identified using blood pressure and echocardiography instruments.

Ventricular tachycardia (VT) and ventricular fibrillation (VF) are known ventricular cardiac arrhythmias (VCA) that promote fast defibrillation treatment for the survival of patients and are defined as shock-oriented signals, perhaps the most common source of sudden cardiac arrest (SCA). The majority of existing VCA classifiers confront a difficult challenge of accuracy rate, which has generated the issue of continuous detection and classification approaches. In light of this, the authors present a feature learning strategy that uses the improved variational mode decomposition technique to detect VCA on ECG signals. The following SCA consists of a deep convolutional neural network (deep CNN) as a feature extractor and bat-rider optimization algorithm (BROA) as an optimized classifier. The MIT-BIH arrhythmia database is used to examine the approaches, and the analysis depends on performance indicators such as accuracy, specificity, sensitivity, recall, and F1-score.

Assistive devices and technology reduce a person's dependency on others while also improving the overall quality. Wheelchairs, visual aids, hearing aids, and specialist computer software and hardware systems help the elderly and disabled improve their hearing, vision, mobility, and communication. Assistive technology, for example, provides enormous opportunity to improve the effectiveness of both health and social care delivery. 'Low-tech' products like memory aides and digital calendars, as well as 'high-tech' items like health tracking gadgets and wearables, are examples of assistive technologies. Assistive devices can be used to improve quality of life, improve lifestyle, and boost independence, depending on the type of device. Patient and caregiver acceptance of technology is influenced by a variety of factors, including perceived skills and competencies in utilizing the device, expectancies, trust, and reliability.

Various types of heart diseases and conditions leading to increasing chance of heart attack have been a serious concern all over the world. Several factors like blood pressure, cholesterol, diabetes, obesity can affect the heart, and thus, those should be monitored regularly to prevent the chance of heart attack in people of different age groups. This chapter at first has analyzed different existing benchmarks of heart attack analysis. Being motivated by the shortcomings of the state-of-the-art literature and to address the challenges, it has introduced support vector machine, the most popular supervised machine learning algorithm to classify the chance of heart attack using a dataset downloaded from Kaggle. The experimental result has been evaluated using different performance metrics, including accuracy, error rate, precision, recall, F1 score. Finally, the performance has been compared with the existing related works also to validate its effectiveness and efficiency in real-time heart attack prediction.

Cardiovascular disease (CVD) is a medical condition that leads to risk of heart disease such as stroke or cardiac arrest. Cardiac attack is a medical condition found in different age groups irrespective of gender. In a clinical study, there are many ways of interpreting the risk factors. The most common risk factors indicating sudden cardiac arrest are glucose, body mass index (BMI), and habitation such as smoking. The difficulties faced by the clinicians are the primary focus of this study. The complexity in clinical stages in examination of medical condition needs to be resolved considering the symptoms and other risk factors leading to sudden cardiac arrests and deaths. Thus, validation of clinical examination at times is a laborious and time-consuming process, while tracking patient history is voluminous over a period of time. This chapter presents the analysis of risk factors causing cardiovascular diseases. The statistical significance and clinical validation of the computer-assisted tool is presented in this study.

Recent surveys suggest that the majority of the world's population is unconcerned with their health. Aside from a hectic lifestyle, research reveals that stress is also a component in the development of many diseases. Sudden cardiac arrest and death (SCD) is a major public health concern that jeopardizes patient safety. As a result, detecting such illnesses only by ECG is difficult. The Bayesian Dirichlet equivalence score, AIC (akaike information criterion), and MDL (maximum description length) scores make up the variable-order Bayesian network (VOBN). On the basis of HRV (heart rate variability) acquired from ECG and using a hybrid classifier to identify SCD patients from normal patients, this study predicts sudden cardiac arrest before it occurs within 30 minutes. The validity of the suggested study is checked using the physionet database of cardiac patients and normal people, as well as the Cleveland dataset. The proposed method achieves 97.1% accuracy, 96.2% precision, 89.8% recall, 84.82% F1-score, 54.66% AUC, and 45.92% ROC, according to the results.

Recently, there has been growing attention to the advances in the areas of electronic and biomedical engineering and the great applications that these technologies can offer mainly for health diagnosis and monitoring. In the past decade, deep learning (DL) has revolutionized traditional machine learning (ML) and brought about improved performance in many fields, including image recognition, object detection, speech recognition, and natural language processing. This chapter discusses detection of heart disease using deep learning techniques. Here the input data has been collected based on wearable device-collected data with IoT module. This data has been preprocessed using adaptive histogram normalization, and the authors segment the image based on threshold method using Ostu thresholding technique. The segmented image feature has been extracted using generative adversarial network and classification of extracted features using deep residual network. The experimental analysis is obtained by the proposed GAN_DRN in terms of accuracy as 96%, precision of 85%, recall of 80%, F-1 score of 71%, and AUC of 75%.

Preface

Machine learning approaches have great potential in increasing the accuracy of cardiovascular risk prediction and avoiding unnecessary treatment. The application of machine learning techniques may improve heart failure outcomes and management, including cost savings by improving existing diagnostic and treatment support systems. Additionally, artificial intelligence (AI) technologies can assist physicians in making better clinical decisions, enabling early detection of subclinical organ dysfunction, and improving the quality and efficiency of healthcare delivery. Further study on these innovative technologies is required in order to appropriately utilize the technology in healthcare.

Leveraging AI Technologies for Preventing and Detecting Sudden Cardiac Arrest and Death provides insight into the causes and symptoms of sudden cardiac death and sudden cardiac arrest while evaluating whether artificial intelligence technologies can improve the accuracy of cardiovascular risk prediction. Furthermore, it consolidates the current open issues and future technology-driven solutions for sudden cardiac death and sudden cardiac arrest prevention and detection. Covering a number of crucial topics such as wearable sensors and smart technologies, this reference work is ideal for diagnosticians, IT specialists, data scientists, healthcare workers, researchers, academicians, scholars, practitioners, instructors, and students.

This book serves as an instant ready reference to researchers and professionals working in the area of AI technologies for preventing and detecting sudden cardiac arrest and death.

ORGANIZATION OF THE BOOK

The book is organized into 10 chapters. A brief description of each of the chapters follows:

Chapter 1

The majority of heart disease-related deaths are caused by sudden cardiac death. It is most common in adults between the ages of 35 and 45. Every day, one thousand people are estimated to be involved in emergencies. The number of ongoing challenges and causes of death in the United States remains unchanged. As a result, improved preventive strategies for sudden cardiac arrest and death are required. The majority of deaths occur in emergency rooms or outside of hospitals. The causes are typically unexpected, and mortalities in just 60 minutes of the appearance of illness. This chapter goes into detail about the symptoms, causes, and risk factors for sudden cardiac arrest. As a result, raising public awareness about the importance of prevention strategies is an hourly need.

Chapter 2

People around the world are at risk from chronic diseases like cancer, heart disease, and diabetes. When it comes to sudden cardiac arrest, many people have recently become increasingly concerned. The main cause of death in the world is heart disease. Because it needs both experience and advanced knowledge, predicting heart disease is a difficult assignment, Sensor values are being collected for heart disease detection and prediction using the Internet of Things (IoT), which has recently been implemented in healthcare systems. In order to achieve a continuous remote cardiac monitoring system, IoT and wireless technology have advanced significantly over the past several years. The use of various sensors, such as electrocardiograms (ECGs), thermometers, and blood pressure monitors, to collect important body signals and diagnose illnesses has resulted in the creation of a wireless body area network. The diagnosis of cardiac disease findings is low inaccuracy. Our goal is to highlight IoT-driven technologies that have been used in the literature for diagnosing and forecasting heart disease.

Chapter 3

AI is used for alerting people who are suffering from heart problems. The patient's language, sound, ascent, voice, and other patterns are used to analyze an audio call for analyzing the heart patient's problems. CPR and defibrillation treatment are used. Delay in sudden cardiac arrest can create problems in the brain, and fatal implications might be there. Biosensors are recommended for heart patients, and they can wear on the wrist to detect hypertrophic cardiomyopathy. The biosensor helps in identifying Hypertrophic cardiomyopathy in heart patients. This condition or disease occurs because of cardiac muscle thickening. This is the reason for heart failure, stroke, and fatality in heart patients. The other observation is outflow tract obstruction in the heart patients who had sudden cardiac deaths. This happens in patients who have blood pressure and can be identified using blood pressure and echocardiography instruments.

Chapter 4

Ventricular tachycardia (VT) and ventricular fibrillation (VF) known as Ventricular Cardiac Arrhythmias (VCA) promote fast defibrillation treatment for the survival of patients and are defined as shock-oriented signals, perhaps the most common source of Sudden Cardiac Arrests (SCA). Information on the linkage between air pollution with the risk of out-of-hospital cardiac arrest (OHCA). The majority of existing VCA classifiers confront a difficult challenge of accuracy rate, which has generated the issue of continuous detection and classification approaches. In light of this, we present a feature learning strategy that uses the improved variational mode decomposition technique to detect VCA on ECG signals. The following SCA consists of a deep convolutional neural network (deep CNN) as a feature extractor and a Bat-Rider optimization algorithm (BROA) as an optimized classifier. The MIT-BIH Arrhythmia Database is used to examine the approaches, and the analysis depends on performance indicators such as accuracy, specificity, sensitivity, recall, and F1 score.

Chapter 5

Assistive devices and technology reduce a person's dependency on others while also improving the overall quality. Wheelchairs, visual aids, hearing aids, and specialist computer software and hardware systems help the elderly and disabled improve their hearing, vision, mobility, and communication. Assistive technology, for example, provides enormous opportunities to improve the effectiveness of both health and social care delivery. 'Low-tech' products like memory aides and digital calendars, as well as 'high-tech' items like health tracking gadgets and wearables, are examples of assistive technologies. Assistive devices can be used to improve quality of life, improve lifestyle, and boost independence, depending on the type of device. Patient and caregiver acceptance of technology is influenced by a variety of factors, including perceived skills and competencies in utilizing the device, expectancies, trust, and reliability.

Chapter 6

Various types of heart diseases and conditions leading to an increased chance of heart attack have been a serious concern all over the world in recent times. Several factors like blood pressure, cholesterol, diabetes, and obesity can affect the heart and thus, those should be monitored regularly to prevent the chance of heart attack in people of different age groups. This chapter first has analyzed different existing benchmarks of heart attack analysis. Being motivated by the shortcomings of the state-of-the-art literature and to address the challenges, it has introduced Support Vector Machine, the most popular supervised machine learning algorithm to classify the chance of heart attack using a dataset downloaded from Kaggle. The experimental result has been evaluated using different performance metrics, including accuracy, error rate, precision, recall, and F1 score. Finally, the performance has been compared with the existing related works also to validate its effectiveness and efficiency in real-time heart attack prediction.

Chapter 7

Cardio Vascular Disease (CVD) is a medical condition that leads to the risk of heart diseases such as stroke or cardiac arrest. Cardiac Attack is a medical condition found in different age groups irrespective of gender, the severity of risk is more common. In a clinical study, there are many ways of interpreting the risk factors. The most common risk factors indicating sudden cardiac arrest are glucose, body mass index (BMI), and habitation such as smoking. The difficulties faced by the clinicians are the primary focus of this study. The complexity of clinical stages in the examination of medical conditions needs to be resolved considering the symptoms and other risk factors leading to sudden cardiac arrests and deaths. Thus, validation of clinical examination at times is a laborious and time-consuming process, while tracking patient history is voluminous over a period of time. This chapter presents the analysis of risk factors causing cardiovascular diseases. The statistical significance and clinical validation of the computer-assisted tool are presented in this study.

Chapter 8

Recent surveys suggest that the majority of the world's population is unconcerned with their health. Aside from a hectic lifestyle, research reveals that stress is also a component in the development of many diseases. Sudden cardiac arrest and death (SCD) is a major public health concern that jeopardizes patient safety. As a result, detecting such illnesses only by ECG is difficult. The Bayesian Dirichlet equivalence score, AIC (Akaike information criterion) and MDL (maximum description length) scores make up the Variable-order Bayesian network (VOBN). On the basis of HRV (Heart rate variability) acquired from ECG and using a Hybrid classifier to identify SCD patients from normal patients, this study predicts sudden cardiac arrest before it occurs within 30 minutes. The validity of the suggested study is checked using the physionet database of cardiac patients and normal people, as well as the Cleveland dataset. The proposed method achieves 97.1% accuracy, 96.2% precision, 89.8% recall, 84.82% F1-score, 54.66% AUC, and 45.92% ROC, according to the results.

Chapter 9

Recently, there has been growing attention to the advances in the areas of electronic and biomedical engineering and the great applications that these technologies can offer mainly for health diagnosis and monitoring. In the past decade, deep learning (DL) has revolutionized traditional machine learning (ML) and brought about improved performance in many fields, including image recognition, object detection, speech recognition, and natural language processing. This chapter discusses the detection of heart disease using deep learning techniques. here the input data has been collected based on wearable device collected data with the IoT module. This data has been pre-processed using adaptive histogram normalization and segmented the image based on the threshold method using Ostu thresholding technique. The segmented image feature has been extracted using a generative adversarial network and the classification of extracted features using a Deep Residual Network. The experimental analysis obtained by the proposed GAN_DRN in terms of accuracy was 96%, precision of 85%, recall of 80%, F-1 score of 71%, and AUC of 75%.

Chapter 10

Heart disease is estimated to be the major cause of death among the middle-aged population, worldwide. Researchers assess huge volumes of medical data using a variety of statistical, machine learning, and deep learning methods, supporting healthcare practitioners in predicting heart illness. This work aims to predict the likelihood of people developing heart disease using a wearable wristband that can record Photoplethysmography (PPG) signals. Cardiovascular features extracted from the PPG signal are used to train the prediction algorithm. It enables the patient to self-monitor their health and take precautionary measures and treatment at the onset of symptoms of the disease. Random Forest, Convolutional Neural Network, and Long Short-Term Memory networks are trained using publicly available databases comprising both affected and standard parameters and thereby used for comparison with the acquired sensor data for predictive analysis.

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Introduction

The number of persons afflicted by severe medical conditions is on the rise as a result of global population growth and lifestyle shifts. This has resulted in an increase in the number of people attending hospitals, putting a burden on the Medicare healthcare system in the process. A growing need for remote health care systems that can assist with these challenges has resulted as a result of these developments. The breakthroughs in the disciplines of electrical and biomedical engineering, as well as the myriad applications that these technologies can give, have recently received considerable attention, notably in the areas of health diagnosis and monitoring. Smartphones and wearable sensors are now available at reasonable prices to a large number of people all around the world. When used in conjunction with artificial intelligence technologies, these devices can be utilized to monitor and diagnose individuals suffering from heart illnesses, reducing the number of hospital visits and improving people's quality of life. Cardiovascular disease, also referred to as CAD or coronary artery disease, is defined as a group of problems caused by plaque build-up in the walls of arteries, which causes the arteries to narrow over time, making blood flow more difficult and increasing the risk of heart attack and stroke. The American Heart Association defines CAD as a group of problems that include heart attack and stroke, as well as heart failure and other complications.

It is possible to prevent sudden cardiac death (SCD), which is a significant cause of death and morbidity. It is expected to have a global yearly prevalence of 5.2 million individuals, according to projections. SCD is defined as a type of heart failure that occurs within 24 hours of the onset of symptoms, or within 24 hours of the last time, the sufferer was seen in a healthy state. Those suffering from heart failure find that their hearts stop pumping or that their hearts stop beating adequately, resulting in the cessation of oxygen delivery to the entire body, resulting in a deficit of blood flow. Despite the fact that ischemic brain damage begins within seconds following cardiac arrest, there is only a short window of opportunity for treatment to prevent SCD from occurring. Despite the fact that ischemic heart illness accounts for the vast majority of SCD patients, primary arrhythmic disorders are common in people under the age of 30. Regardless of the underlying cause of the circulatory collapse, an early electrocardiographic (ECG) diagnosis of abnormal electrical rhythm versus normal electrical rhythm is crucial for successful treatment. The shockable ECG signals such as VF and VT can be restored to normal sinus beat by restoring the right heart pumping rate. However, in non-shockable beats such as asystole or pulseless electrical impulses, where electromechanical divergence inhibits cardiac shrinkage despite an ordered electrical heart rate, shock therapy will not restore sinus rhythm or cardiovascular flow, and thus will not be effective. Computer-Aided Arrhythmia Classification (CAAC) techniques have been frequently integrated into the CAAC scheme, which improves overall accuracy by smart identification of shockable ECG rhythms, while also providing certain prognosis management that is premised on the appropriate ECG analysis throughout the cardiac arrest. Most SCDs occur outside of the hospital, where ECG identification and treatment are not available, resulting in poor survival rates and brain outcomes abnormalities, as well as other complications. Devices that distribute electrical pulses to the heart in the event of cardiac arrest are routinely used to re-establish a stable heartbeat in the event of cardiac arrest. Accurate ECG rhythm diagnosis is becoming increasingly important, prompting the development of novel CAAC systems and associated AI-based approaches.

Techniques based on machine learning have a lot of potential for improving the accuracy of cardiovascular risk prediction and avoiding the use of needless treatment. The application of machine learning techniques to heart failure outcomes and management may result in cost savings by improving existing diagnostic and treatment support systems, as well as improved heart failure outcomes and management. Besides that, artificial intelligence technologies can assist physicians in making better clinical judgments, enabling the early detection of subclinical organ disease, and enhancing the quality and efficiency of healthcare delivery services. Further research into these cutting-edge technologies is required in order to make optimal use of the technology in the healthcare setting.

The study, *Leveraging Artificial Intelligence Technologies for Preventing and Detecting Sudden Cardiac Arrest and Death*, provides insight into the causes and symptoms of sudden cardiac death and sudden cardiac arrest while also evaluating whether artificial intelligence technologies can improve the accuracy of cardiovascular risk prediction. Furthermore, it consolidates the present unresolved challenges as well as future technology-driven solutions for sudden cardiac death and sudden cardiac arrest prevention and detection in addition to sudden cardiac death and sudden cardiac arrest. With chapters on critical topics such as wearable sensors and smart technologies, this reference work is ideal for diagnosticians, IT specialists, data scientists, healthcare workers, researchers, and academicians, as well as professionals in the fields of academia, and research.

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Chapter 1
SCA and SCD:
Causes, Symptoms, Prevention, and Detection

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ABSTRACT

The majority of heart disease-related deaths are caused by sudden cardiac death. It is most common in adults between the ages of 35 and 45. Every day, one thousand people are estimated to be involved in emergencies. The number of ongoing challenges and causes of death in the United States remains unchanged. As a result, improved preventive strategies for sudden cardiac arrest and death are required. The majority of deaths occur in emergency rooms or outside of hospitals. The causes are typically unexpected, and mortalities in just 60 minutes of the appearance of illness. This chapter goes into detail about the symptoms, causes, and risk factors for sudden cardiac arrest. Raising public awareness about the importance of prevention strategies is an hourly need.

1 HEART DISEASE AND SUDDEN CARDIAC ARREST (SCA): AN OVERVIEW

Heart diseases affect heart valves, walls, chambers, and muscles. These are termed congenital heart diseases, cardiomyopathy, and heart valve disease. Heart disease exists from birth and complexity grows as one age (Empana et al., 2022). It has to be monitored regularly. Structured heart diseases are abnormalities or issues that happen to the heart leading to health problems. This disease can affect anyone no matter his or her gender, race, etc. Most commonly family history, pregnancy, alcohol consumption, and viral infections can cause these diseases. Adults of age greater than 75, 10% face these conditions (Norrish et al., 2022). Valvular regurgitation is the most common among them. The congenital heart conditions make the pumping of the blood difficult. Blood with nutrients and oxygen enables your body cells to survive. Without this, the body organs and tissues may be damaged leading to many health problems and symptoms (Kim et al., 2022). The major causes that develop abnormality and heart disease include drug addiction, aging, where heart valves get deposited with calcium, autoimmune diseases, high blood pressure, high dose radiation exposures, plaque in arteries, etc. These do not have any signs or symptoms

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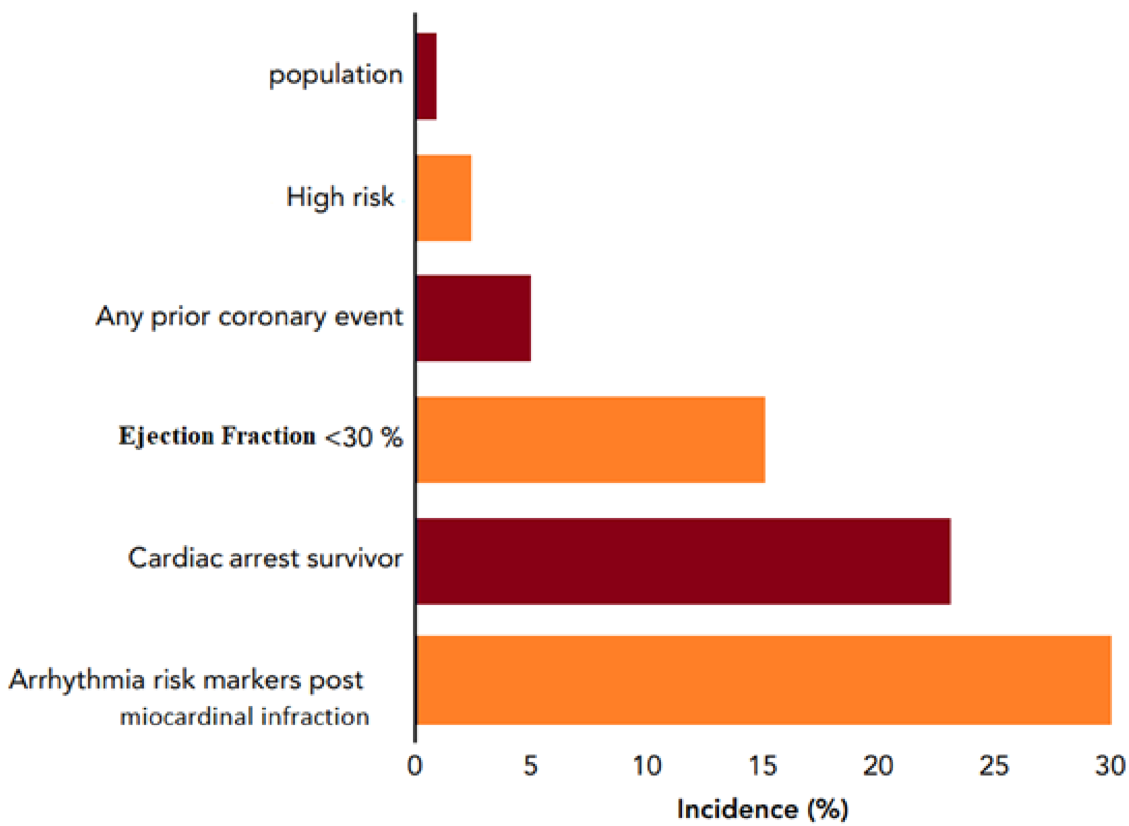
and suddenly patients may get chest pain, tightness, dizziness, fainting, fatigue, irregular heartbeats, kidney dysfunction, and swelling in the abdomen. The healthcare professionals diagnose the disease during the pregnancy check. The fetal echocardiogram is used to detect structural heart diseases. This technique employs acoustic signals to analyze the baby's heart's functions and features. In a stethoscope, on listening there exists a heart murmur in children and adults. The various tests cardiologists perform include cardiac catheterization, coronary angiogram, echocardiogram, electrocardiogram, exercise stress test, Holter monitor, and imaging tests. On cardiac catheterization, the cardiologists insert a small tube through the artery. This tests pressures within your heart chambers. The heart and blood vessels are seen in close-up images. Cardiologists perform angiography by injecting dye that caterer into the blood vessels. The heart-pumping action can be checked by using an echocardiogram. It is necessary that during pregnancy you reduce the risk of the child having congenital heart diseases. For which it is necessary to maintain a healthy diet, exercise, reduce stress, etc. with heart diseases many people have led stronger lives. If you eat well and exercise regularly, you are helping to prevent coronary heart disease, which is caused by plaque deposits in the arteries and can end up causing chest pain as well as cardiac arrest. A different issue is structural cardiovascular disease. It's a name used to explain deficiencies or abnormalities in the heart's structure, such as its valves. The excellent thing is that structural cardiovascular disease treatments are getting better. While treatment usually is the best choice in some cases, non-invasive catheter-based treatments have decided to take care extra pleasant for patients, with fewer problems and faster improvements. It is always necessary to keep the heart healthy and reduce complications. A healthy lifestyle and regular monitoring can help to lead a fruitful life. Always early diagnosis may lead to successful treatment. People with heart diseases are treated with open-heart surgery (Tu et al., 2022). Open-heart surgery may have medium to high risk. Minimal invasive procedures, short procedure time, no scarring, less blood loss, decreased pain, etc. increase the faster recovery and reduce complications. Minimal invasive procedures allow evaluating the valve functions and blood flow. The mitral clip is designed to treat the whole heart. It is a metal clip covered with polyester fabric. The clip will prevent the blood from flowing in the wrong direction. Today low and middle-income countries face a burden of structural heart diseases. The condition is rheumatic heart disease, Chagos disease, etc. Treatments are readily available in high-income countries. Interventional technology for the diagnosis of structural heart disease is continually growing and has become standard practice in a rising number of centers around the world. The medical community has come to accept the term "structural cardiovascular disease" as a disease category over the last decade. The chronic conditions and equipment described in the previous section, demonstrate that coronary heart intervention incorporates a wide range of treatment options. Considering that the majority of these processes rely on catheter and wire exploitation skills honed by cardiac and peripheral vascular interventionists, it logically follows that interventional cardiologists can also treat structural disease. Nevertheless, there are significant structural disease-specific issues that make the transition more complicated. The first consideration is the role of adjunct therapy image analysis and preprocedural evaluation in structural heart disease treatment. Percutaneous treatment of these procedures is undoubtedly reliant on hemodynamic and endoscopic evaluation, which interventional cardiologists are well-versed in. However, cardiac intervention optimization relies mainly on soft-tissue imaging, entailing mastery of additional modalities such as echocardiography. Furthermore, different imaging modalities, such as intracardiac echocardiography for PFO and ASD closure and transesophageal echocardiography for percutaneous valve implantation, are better suited to different disease processes. The volume of patients and procedures is a second issue (Sridharan et al., 2022). While large catheterization laboratories perform thousands of coronary interventions per year, structural heart volume is much lower, with even recognized high-volume experts trying to perform only 200–300 instances per year. Furthermore, many reputed and reliable centers do not perform cardiac interventions, and while some centres may be considered “centres of excellence” for one type of structural cardiovascular disease, they may have no expertise with another. This has significant ramifications for technology training and dissemination, as the goal of training is to ensure a minimum common standard of cognitive understanding and technical skills. As a result, even before their training is completed, many interventional trainees will not have received the necessary training to perform these procedures (Schupp et al., 2022). Furthermore, once out of training, maintaining the necessary volume to remain current and proficient is an entirely different issue. A third challenge is the broad range of structural heart disease and the subtle variability within each disease process. Percutaneous treatment of ASD and PFO, for example, entails closing communication between two chambers using similar devices and implantation techniques. However, not all machines are appropriate for every lesion, and understanding the nuances and applying the best technology for each lesion requires a certain level of expertise. In addition, percutaneous treatment of valvular heart disease necessitates a distinct knowledge base and skill set (Norrish et al., 2022). Recognizing the inherent difficulties of being a true expert in everything paves the way for subspecialized centres and individuals to emerge, even within the field of structural heart intervention (Lee et al., 2022). A birth defect that connects the right and left atriums are known as the foramen ovale. The septae, which are physiologically important during the embryonic period, close quickly after birth and fuse together in the majority of people within two years. In the vast majority of children, the ductus closes spontaneously shortly after birth; however, persistent patency occurs in approximately 1 in 2000 births (Harmon et al., 2022). Most PDAs in children and adults can be closed transcatheter. An occluder can be placed from either the pulmonary artery or the aorta with excellent results. In patients with non-valvular atrial fibrillation, embolic stroke is associated with left atrial thrombi (Chugh et al., 2022). The goal of either surgical or percutaneous intervention is to improve systolic lowering wall tension and contradictory movement by downsizing and correcting the geometry of the left ventricle. Hundreds of thousands of prosthetic valves are implanted each year. The fact that it is technically difficult is one of its primary limitations. The mitral apparatus, which includes the mitral valve leaflets, annulus, chordae, papillary muscles, and ventricle, is a complex structure. A slew of percutaneous devices designed to treat mitral regurgitation is currently in the works. All of the valve leaflets, the annulus, and the ventricle itself are potential targets. Percutaneous therapy for mitral regurgitation faces significant challenges due to the variety of underlying causes of mitral regurgitation, as well as the fact that individual devices can only target one mechanism. Over the last decade, the therapeutic options for symptomatic HOCM patients have expanded due to the introduction of percutaneous transluminal septal myocardial ablation. This interventional procedure causes an alcohol-induced septal infarction, which is anatomically and hemodynamically similar to surgical myectomy. Although no randomized trials comparing percutaneous and surgical septal ablation have been conducted, it appears that both treatment options produce comparable hemodynamic and clinical outcomes (Remme et al., 2022). A growing number of additional structural heart disease processes are being approached percutaneously in adult patients.

Sudden Cardiac Arrest and Death is an unexpected loss of heart functioning. The largest cause of death where around 3,25,000 adults every year. Most heart diseases based deaths are due to sudden cardiac death. It is widely seen among adults of the age group between 35 to 45 years. Commonly seen among males rather than females. Rarely seen in children, only 1 to 2 in children are affected every year. American Heart Association’s Heart and Stroke statistics reported in the year 2020 showed that heart diseases and strokes have reduced. Sudden cardiac arrest remains a major public health challenge. The incidents of emergency cases are estimated to be one thousand people every day(Rohila & Sharma, 2020). Only ten percent of the cardiac arrest survival cases and hospital discharges are seen. The number of ongoing challenges and causes of death nationwide remains as such. Best estimates are provided on clinical trials (Harhash et al. 2021).

Globally sudden cardiac arrest and death are considered public health problems. Around 15-20% of deaths occur due to sudden cardiac arrest (Wong et al., 2019). Most death **occurs within one hour of the identification of the symptoms** and 24 hours of the unwitnessed symptoms. The majority of patients are found to be with heart block (Srinivasan & Schilling, 2018). There have been many improved preventive strategies and practices in hospitals to prevent cardiovascular mortality rates. Risks relevant to this are highlighted (Yadav & Jadhav, 2021). The major challenge clinicians face is the known cardiac disease risks depicted in Figure 1 (Srinivasan & Schilling, 2018). However, low-risk patients are low and the highest risk is high (Khairy et al., 2022). Therefore, improved preventive strategies concerning sudden cardiac arrest and death have to be addressed. Despite various IC agents medical therapy still preventive measures for SCD (Sudden Cardiac Death) remains a challenge (Marijon et al., 2022).

Figure 1. SCD –Traditional risk factors



From the US community report from hospitals, it has been reported that sudden cardia arrest is seen among young people in the age group between 5-34 (Blom et al., 2019). These are due to obesity, hypertension, smoking, and diabetes. Most commonly around 58% of risk factors are observed. The major clinical implication is due to obesity (Jang et al., 2020). In sudden cardiac arrest, the patient collapses with a low pulse rate. The emergency medical services although provided 90% of cases go to the mortality stage. Thus in the case of societal perspective, it is identified as a major public health issue. Prevention of this remains a challenge (Jayaraman et al., 2018).

2 SUDDEN CARDIAC ARREST – SYMPTOMS AND CAUSES

A heart attack is not a sudden cardiac arrest. It happens when the coronary arteries become blocked, preventing oxygen-rich blood from flowing. The malfunctioning of the heart becomes dangerous (Andersen et al. 2019). The ventricles may flutter without delivering the required blood to the body. Once the blood flow stops, the consciousness of the person will be lost. The following are immediate and severe signs of sudden cardiac arrest:

- Sudden demise
- There is no pulse
- There is no way to breathe
- Consciousness loss

Other indications and symptoms may appear before sudden cardiac arrest. These could include the following:

- Uncomfortable chest
- Breathing problems
- Weakness Heart

Sudden cardiac arrest, on the other hand, frequently occurs without warning. Pain or discomfort in the chest Palpitations in the heart Heartbeats that are fast or irregular Wheezing that isn't related to anything (Sawyer et al., 2020). There requires immediate emergency treatment. Sudden cardiac death occurs within an hour of the set of symptoms. Coronary artery disease is the common cause. The other is due to alcoholism, obesity, and fibrosis (Zorzi et al., 2020).

Ischemic Heart Disease
  - Myocardial infarction
  - Anomalous coronary origin
  - coronary spasm

Inherited Channelopathies
  - Long QT syndrome (LQTS)
  - Short QT syndrome (SQTS)
  - Brugada syndrome
  - Early repolarization syndrome

- ◦ Catecholaminergic polymorphic ventricular tachycardia (CPVT)

Cardiomyopathies
- ◦ Alcoholic
- ◦ Hypertrophic
- ◦ Idiopathic
- ◦ Obesity-related
- ◦ Fibrotic
- ◦ Arrhythmogenic right ventricular cardiomyopathy (ARVC)
- ◦ Myocarditis

Heart Failure
- ◦ Nonpreserved ejection fraction (EF) systolic heart failure (EF less than 35%)

Valve Disease
- ◦ Aortic stenosis

Congenital Diseases
- ◦ Tetralogy of Fallot

Cardiac deaths are sudden. The changes are frequently seen in children, adolescents, and adults. Coronary anomalies are found on autopsies (Zhao et al., 2019). This affects around three lakh to four lakh individuals every year. The most prevalent is that 19% of children and 30% of adults are affected due to this (Sandroni et al., 2018). The highest prevalence is due to myocardial infractions. Sudden death is seen in men of all age groups between 45 to 54 years. Men are affected higher than women (Osman et al., 2019). There lie racial differences among the adolescents affected by sudden cardiac death. Most of the deaths occur either in emergency rooms or outside the hospital. The causes are usually unexpected and deaths occur within an hour of the onset of symptoms. World health organization reported many cases of acute myocardial infections and the influence of cardiac causes. Death is seen in 12% within two hours on the onset of the symptoms and 80% on the duration of less than a day. These are stable, neutral, and unexpected. The disease causes can be natural or violent. The differences may be difficult to find and analyze the death causes. The condition is life-threatening and may lead to sudden death. Some of the causes of sudden cardiac death are presented in Table 1.

Table 1. Causes of sudden cardiac death

Immediate cause	Underlying causes	Mechanisms
Acute ischemia	Coronary atherosclerosis, nonatherosclerotic coronary diseases, aortic stenosis	Ventricular fibrillation, bradycardia, electromechanical dissociation (usually end stage or postresuscitation)
Infiltrative diseases	Inflammatory (myocarditis), scars (healed infarcts, cardiomyopathy)	Ventricular fibrillation, bradyarrhythmias (uncommon[a])
Cardiac hypertrophy	Hypertrophic cardiomyopathy, systemic hypertension, idiopathic concentric left ventricular hypertrophy, aortic stenosis	Ventricular fibrillation, bradyarrhythmias (uncommon)
Cardiac dilatation (congestive failure)	Dilated cardiomyopathy, chronic ischemia, systemic hypertension, aortic insufficiency, mitral insufficiency	Ventricular fibrillation, bradyarrhythmias (uncommon)
Cardiac tamponade	Rupture myocardial infarct, aortic rupture	Electromechanical dissociation
Mechanical disruption of cardiac blood flow	Pulmonary embolism, mitral stenosis, left atrial myxoma	Electromechanical dissociation, ventricular fibrillation
Global myocardial hypoxia	Severe ischemic heart disease, aortic stenosis	Baroreflex stimulation with bradyarrhythmias, ventricular tachyarrhythmias
Acute heart failure	Massive myocardial infarct, rupture papillary muscle, acute endocarditis with chordal or leaflet rupture, MVP with chordal rupture	Electromechanical dissociation, ventricular fibrillation
Generalized hypoxia	Pulmonary stenosis, pulmonary hypertension	Bradyarrhythmias
Vasovagal stimulation	Neuromuscular diseases	Baroreflex stimulation with bradycardia
Preexcitation syndrome	Accessory pathways	Atrial fibrillation → ventricular fibrillation
Long QT syndrome	Congenital and acquired states	Ventricular fibrillation (torsades de pointes)
Heart block	AV nodal scarring, inflammation, tumor	Bradycardia → ventricular fibrillation

Infants and Children

Based on the age of the patient the death causes vary. The infants of sudden unexpected death are seen under one year of age. The causes of death are found under clinical examinations. Every year less than twenty patients die suddenly. The primary cause of death was ectopic aortic origin. Mostly it is not due to heart disease. Fifty percent of cardiac causes are due to congenital heart diseases. These are represented in Table 2.

Table 2. Causes below 20 years of age

Causes of death, ages 14–20	
Cause of death	
No finding	(30%)
Myocarditis	(13%)
Hypertrophic cardiomyopathy	(12%)
Anomalous coronary artery	(8%)
Complex congenital heart disease	(7%)
Atherosclerosis	(5%)
Dilated cardiomyopathy	(5%)
Floppy mitral valve	(5%)
Idiopathic left ventricular hypertrophy	(5%)
Aortic dissection	(3)%
Kawasaki	(3%)
Tunnel coronary artery	(3%)
Hypertensive left ventricular hypertrophy	(2%)

Adolescents and adults

In adolescents and young adults, myocarditis, cardiomyopathies, and coronary artery anomalies are the most common causes of sudden cardiac death in individuals. Few autopsy studies have identified that patients die due to luminal narrowing of coronary arteries. Many cases report severe narrowing on autopsy. Mostly for men above 45 years of age. Ten percent of them suffer due to one vessel disease, three percent due to two vessels, and only one percent from one per vessel. There lies a large number of out-of-hospital deaths. Some are due to hypertension, while in the absence of hypertension there is a sudden increase in the weight narrowing the epicardial arteries. Cardiopulmonary resuscitation (CPR) and defibrillation pass the oxygen to the lungs and brain enabling them to be normal until the heart function restores. Defibrillation is an electric shock to the chest that helps to save a life. On heart beat raised people may feel dizzy. Most of the cases people experience without prior symptoms. Abnormal heart rhythms called arrhythmias are life-threatening and lead to death if left untreated. Many risk factors lead to sudden cardiac arrest. The primary of them are

i) History of the previous occurrence of heart attacks, especially the first six months after the heart attack is crucial. Seventy-five percent of cases turn up due to this reason.
ii) Coronary artery disease due to habits like smoking, family history, high cholesterol, etc. Eighty percent of the cases are linked to these types.

iii) The other risk factors include:
  - Ejection Fraction
  - Family history
  - Blood vessel abnormalities
  - History of congenital heart defects
  - Syncope
  - Heart failure
  - Dilated Cardiomyopathy
  - Hypertrophic Cardiomyopathy
  - Potassium and magnesium changes in blood vessels
  - Obesity
  - Diabetes
  - Recreational drug abuse
  - Stress, shock, and disbelief

People at some point face stressful life events which include natural disasters, life-threatening illnesses, the death of loved ones, etc. Such events cause adversities and lead to several risk factors related to cardiovascular disease. it is being reported that people with psychiatric disorders have the highest risk. The type of stressors, symptoms, and durations are categorized. The major disorders are physical and psychological. The severe and widely studied stress disorders are negative cognition and moods. The other stress reaction includes acute cardiovascular high-risk time.

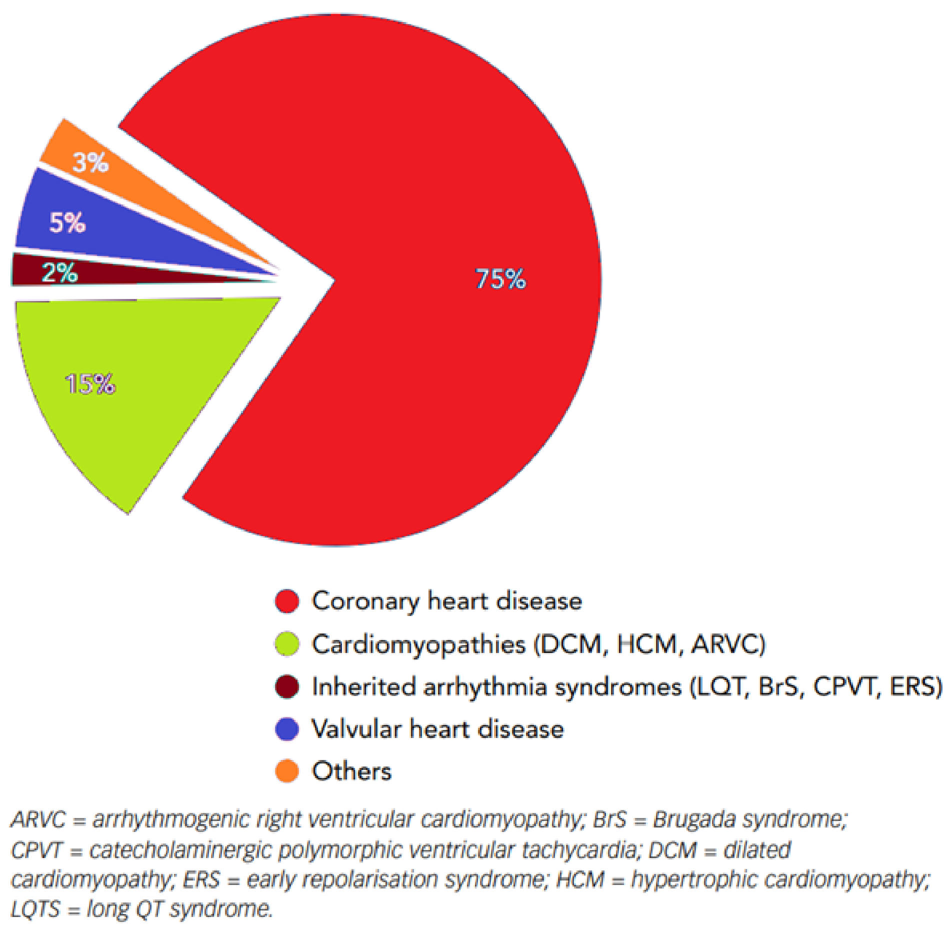
3 SCA: THE CHAIN OF SURVIVAL

Mostly, cardiac arrest occurs outside the hospital. In the case of the United States, those admitted due to cardiac arrest have a survival rate of 8.1%, and those discharged out of the hospital after treatment is only 3.2%. Thus the primary priority is to increase the survival rate (Srinivasan & Schilling, 2018). This includes:

- Introduction to emergency response system
- Analysis of chest compressions at the early stage
- Rapid defibrillation
- Providing advanced life support monitoring
- Post care

The immediate response can be obtained from the prompt action of the bystanders. Public response to cardiac arrest patients can improve survival outcomes. Delay in each second to the hospital reduces their chances of survival. It has been reported that 30, 381 cardiac arrest cases were saved in Sweden with the establishment of immediate emergency medical services (Srinivasan & Schilling, 2018). Also, on discharge from the hospital, it requires a goal-directed post-care. This increases the patient survival rate to 35% (Blom et al., 2019). Early coronary interventions and uninterrupted defibrillation have shown excellent outcomes. However, the awareness of these is important to be raised through public education and community engagement. The patients have to be assessed out of the hospital in considering their collateral history. The various causes of sudden cardiac death are shown in Figure 2. The common cause is ischaemic heart disease. the symptoms include breathlessness, palpitations, chest pain, etc. The risk factors are hypertension, smoking, diabetes, etc. (Blom et al., 2019). The patient has to be taken care of. The use of recreational drugs, psychiatric drugs, etc. is to be enquired about with specific questions (Srinivasan & Schilling, 2018). Additionally, patients' practices in concern to exercise, family history, handling of stress, etc. have to be carefully checked.

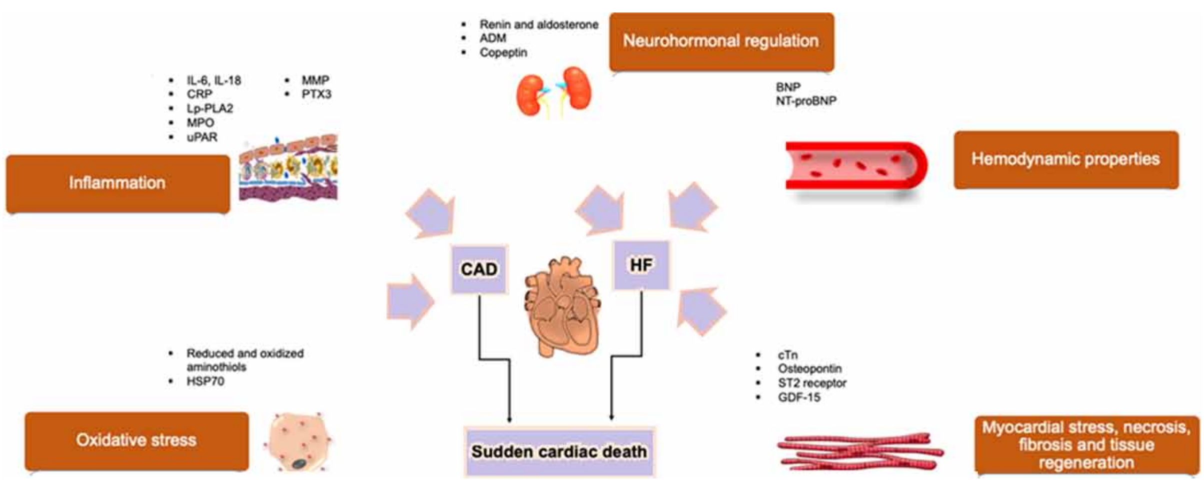
Figure 2. SCD- Causes



4 CARDIAC ARREST: IN HOSPITAL

The high mortality rate is associated with in-hospital cardiac arrest. The United States report in the year 2019 it is addressed that 290000 adults witnessed cardiac arrest in hospital. Cardiac arrest can affect any patient who is hospitalized (Andersen et al., 2019). These usually are not warranted and have been viewed as poor outcomes. This can be reduced with awareness of clinical management. The patients admitted to hospitals have to be checked for various cardiovascular condition states, and neglect to be avoided. This includes causes and prevention of cardiac arrest, treatment during and after cardiac arrest, and prognostication. Considering the patients admitted to the intensive care units eighty percent of them suffer from hypoxic-ischaemic brain injury. Life-sustaining treatments show poor outcomes. This brain injury happens after resuscitation from cardiac arrest. This can be avoided only by minimizing the risk of false predictions. Most of the neurological medications are 100% not specific. The heart serves blood to all parts of the body supplying nutrients and oxygen. The sinoatrial releases external stimuli. These external stimuli can sometimes cause rapid death. In the use of defibrillation, the survival benefits are limited. Detecting and screening with molecular biomass enable early detection. The various type of biomarkers is genetic, protein, and other molecular biomarkers as shown in Figure 3. Genetic biomarkers identify meaningful genomic variants. These screen high penetrance genome variants. The structure of the sodium channel cause delayed or persistent entry of sodium ions across the cell membrane, leading to arrhythmogenic syndromes and SCD. Potassium channels play a significant role in the repolarization of the cardiac action potential. Calcium channels involved releasing the calcium ions to activate the systolic contraction of cardiac muscles. Calcium ion abnormal leak can cause irregular contraction and SCD. High cystine and low glutathione levels increase the mortality risk. Also, the reduction in blood circulation leads to heart failure. Early detection has immense challenges. Biomarkers have been introduced beside them SCD has complex pathophysiology. Thereafter repeated follow-ups are necessary (Osman et al., 2019).

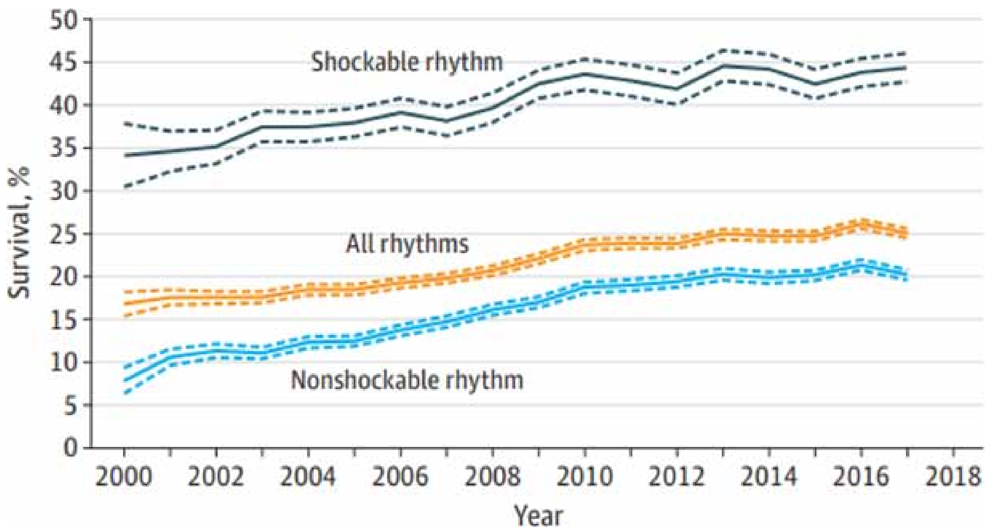
Figure 3. Sudden cardiac death biomarkers



5 DETECTION AND PREVENTION OF CARDIAC ARREST

Traditionally patients with no obvious cause were considered cardia. This is often practiced during clinical diagnosis or post-mortem. The major causes are myocardial infarction, heart failure, etc. as depicted in Figure 2. Most of the patients suffer from respiratory insufficiency. Within one or two days of admission, the patients suffer from respiratory insufficiency (Andersen et al., 2019). Neurological causes are seen only in rare cases. From the data taken from 2000 to 2017 from the guidelines resuscitation registry, the survival graph rate is depicted in Figure 4. The identification of various causes of cardiac arrest will improve the outcomes. Thus the post-cardiac treatment can be planned accordingly. These mechanisms in turn achieve the prevention strategies. For instance, the prolonged prescription of QT in turn leads to arrhythmias. Also, the preventive cause may lead to sepsis (Andersen et al., 2019). There are around 27% of patients suffering from sepsis due to cardiac arrest. Thus prevention is needed for both in-hospital and out-of-hospital patients. It is the first link that connects the survival chain. Early intervention of the disease is the key element for the prevention. Thus each hospital has to depreciate the patient risk and create interventional responses (Andersen et al., 2019).

Figure 4. In-hospital cardiac arrest survival rate up to 2017



Sudden cardiac arrest can be handled as an emergency and has a 90% chance of survival. It is a condition in which the heart suddenly stops beating. When that happens, blood stops flowing to the brain and other vital organs. If it is not treated, SCA usually causes death within minutes. But quick treatment with a defibrillator may be lifesaving. Each minute that passes, the rate drops by 10%. They say most people who survive a cardiac arrest only speak of waking up in hospital afterward, not remembering anything else. However, the warning signs of cardiac death could cause pain. As a result, anyone who sees someone suffering from sudden cardiac arrest should call 911 and start CPR right once. This could potentially save someone's life. The use of an automated external defibrillator (AED) improves the chances of a patient's survival. It can be used to treat and prevent heart issues in the future. You can lower your risk by keeping regular follow-up appointments with your doctor, making specific lifestyle changes, taking medications as directed, and having interventional treatments. It is vital to identify and assess electrocardiogram, ejection fraction, and other factors to prevent repeat incidents. The ejection fraction is a measurement of how much blood is pushed out of the heart per beat. It varies from 55 to 65 percent for a healthy heart. You can reduce your risk of sudden cardiac arrest by making specific lifestyle adjustments to lower your blood pressure and cholesterol levels, as well as managing your diabetes and weight. These are some of them:

- Quit smoking

- Losing weight
- Exercise regularly
- Follow low-fat diet
- Control diabetes

Treatment During and After Cardiac Arrest

During cardia arrest treatment the various treatment procedures include early defibrillation, ventilation, and chest compression. This improves the survival rate (Weissler-Snir et al., 2019). On shockable rhythm, the rapid defibrillation improves the patients. The efficacy of the medication is sparse. During cardiac arrest, airway management is the key component of advanced life support (Tseng et al., 2018). In clinical conditions, ventilation and oxygenation are provided. Post-cardiac causes generally focus on the precipitation cause. The out-of-hospital arrest is usually unpredictable (Andersen et al., 2019). The temperature has to be maintained for at least 24 hours. However, patient characteristics are associated with clinical outcomes (Song et al., 2019). As the age increases the survival rate decreases. The demographic features such as age, sex, race, etc are all associated with the survival outcomes. The other risk factors include pneumonia, hypertension, hepatic dysfunction, etc. on shockable rhythm patients have a two to three times higher survival rate when compared to others. Preventing rhythm increases the survival period by 30 days (Naksuk et al., 2018).

Current Features and Implications

Cardiovascular disease is the leading cause of death and premature death. Indians and Chinese have the highest burden of this disease. this is due to the high prevalence of hypertension. For the past many decades, substantial advances are made in concern data collection, death registration, analysis, etc. Cardiovascular studies based on epidemiology have increased the publication and other sources (Tseng et al., 2018). It has been identified that atherosclerotic cardiovascular disease has increased the burden. In China, in the year 2016 2.4 million deaths were reported. It is necessary to implement strategies for various rehabilitation needs. Another reason is the Ischaemic heart disease which has caused 1.7 million deaths among the Chinese population. Apart from this, there have been reports of hemorrhagic stroke (Tseng et al., 2018). That has declined in recent decades. Although there is a variation in the standardized incidence on the mortality reported there requires a potential strategy. Disease control and prevention have launched a cardiovascular health index guiding the prevention strategies (Krokhaleva & Vaseghi 2019). Many countries have improved their health strategy by transforming sin their economical, social, natural, and environmental lifestyles. However, the most important risk factors contributing are ignored (Tseng et al., 2018). all the medical care and other factors are deeply rooted in their socioeconomic and lifestyle changes. Smoking is a higher risk in both males and females. Apart from this prevalence of hypertension, hyper cholesterol and diabetes mellitus needs to be diagnosed, treated, and controlled (Tseng et al., 2018).

Infants are unlikely to perceive congenital heart disease as a pediatric health priority. However, infant mortality from communicable diseases remains a significant health problem among infants and newborns experiencing rapid and significant human development. Fertility rates rise as the number of women of reproductive age increases. Antenatal prevention efforts can yield relatively modest benefits, but most postnatal interventions for CHD, whether screening or treatment, require the availability of advanced, specialized surgical care. Only 20% of cases have a known cause; multifactorial inheritance has been proposed for cases with unknown etiology. Improved family planning and genetic counseling can aid in the prevention of CHD, particularly if multiple family members are affected and a specific, inheritable genetic disorder is identified. Despite the limited and inconclusive evidence, several general recommendations can be made for women during their reproductive years.

- Completion of rubella vaccination before pregnancy
- Optimal management of metabolic disorders
- Avoidance of medication associated with CHD before and during pregnancy.

Prenatal diagnosis and postnatal screening protocols have aided in the early detection of congenital heart disease. However, timely CHD diagnosis is unusual, and late presentation is the norm. Critical CHD can appear as hypoxemia, hypotension, or both, and is frequently misdiagnosed as neonatal sepsis or pneumonia. CHD is regarded as a significant cause of neonatal and early infant morbidity and mortality by many pediatricians and primary care providers, and intensive targeted education and awareness are required. When deciding whether to implement a screening programme, consider the relatively low overall prevalence of CHD and the low positive predictive value of screening tests. Screening can be done during pregnancy with a fetal echocardiogram or in newborns with a physical exam and pulse oximetry. The different types of screening are prenatal and neonatal screening.

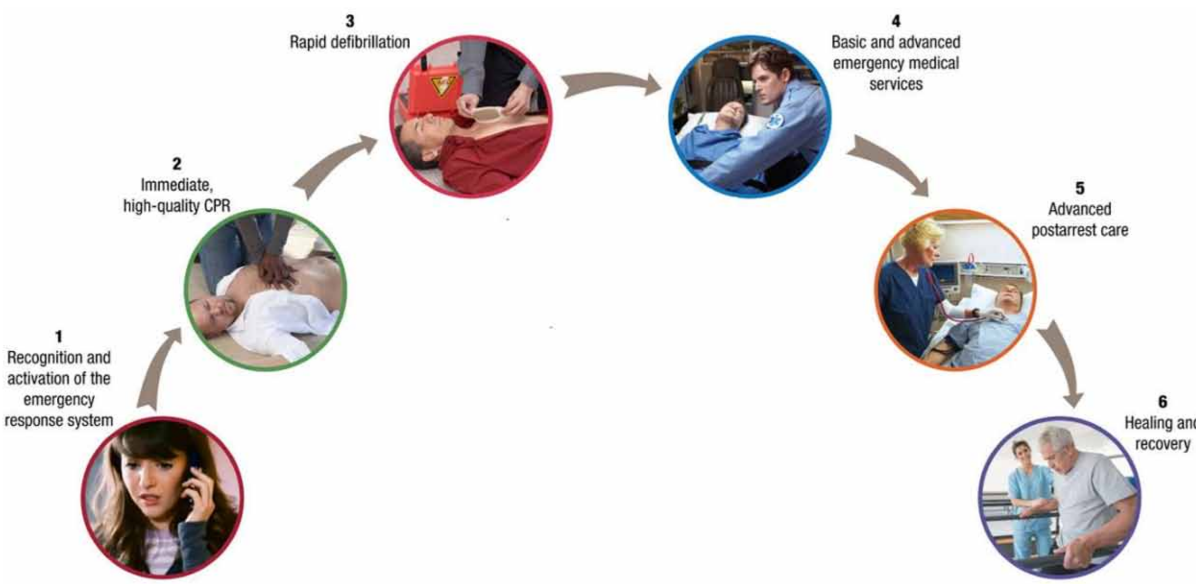
Prenatal screening is commonly used after 14–16 weeks of gestation to screen for CHD and is best suited for relatively severe forms of CHD. The test takes time, and accuracy is heavily influenced by operator expertise and equipment quality. The presence of nuchal translucency on first-trimester antenatal ultrasound may be an alternative screening test, but its sensitivity is low and its utility is likely limited. Treatment options are also limited in the event of a positive screening test. Pregnancy termination may be an option in countries where it is legal and screening begins before 20–24 weeks of gestation. Screening after 20–24 weeks implies the ability to refer patients to a center with a comprehensive pediatric heart programme.

Neonatal screening is the early detection of critical CHD that has the potential to significantly reduce mortality. Early postnatal pulse oximetry detects CHD with greater sensitivity and specificity than clinical examination. Although physical examination has low sensitivity and specificity, one study found several findings that could help identify patients with CHD. Finally, while routine screening echocardiograms for all newborns are impractical, echocardiography can be useful in cases where pulse oximetry or clinical examination indicates a higher than usual risk of CHD. Screening modalities in this age group have not been thoroughly evaluated. The best time to screen for CHD is probably during routine immunization. In this age group, a combination of clinical examination and pulse oximetry can be considered. Children who are underweight or have limited physical capacity must be reevaluated, and the ability to refer suspected cases for confirmatory echocardiography is required.

6 SCA – SURVIVORSHIP

Nowadays people surviving sudden cardiac arrest are getting increased. This includes both children and adults. However, they are associated with physical, emotional, and societal issues. These effects are the after-effects of discharge (Srinivasan & Schilling, 2018). For optimized patient-centered care is essential to coordinate and assess in-hospital patient state and reassess hospital state. It is necessary to anticipate the patient's psychological needs, and provide family care, and support (Peterson et al., 2020). Each patient is unique and they are heterogeneous groups that have to be addressed. The informal communities of survivorship assist and the risk factors related to surveillance and rehabilitation need to be addressed (Srinivasan & Schilling, 2018). Thus, patient support systems must be integrated from short-term to long-term plans. From the literature, it has been identified that cardiac survivors need to focus on individual care (Schmied & Borjesson, 2014). Thus, survivorship focuses on the health and well-being of an individual as depicted in Figure 5.

Figure 5. Cardiac survivorship cycle
(Srinivasan & Schilling, 2018)



The survivorship needs of cardiac arrest survivors require care as shown in Figure 5. On different institutions, they have unique care protocols. In some hospitals, only patients with witnessed arrest and a shockable rhythm are treated with the protocol (Lippi et al., 2018). Once the protocol is decided multiple specialists care for these patients in varied service lines contributing to the post-arrest care. Prior work has demonstrated that most patients do not receive rehabilitation after hospital discharge. Thus, significant opportunities exist to consider the physical, emotional, and cognitive aspects of survivorship to improve outcomes (Zorzi et al., 2020). Thus, the post-care system has helped stakeholders grow beyond functioning as independent silos within the house of medicine. It has encouraged the development of multidisciplinary teams that drive optimal care for patients after cardiac arrest. Quality of life is a broad term describing a person's overall well-being, determined by satisfaction or dissatisfaction with various aspects of life (Zorzi et al., 2020). It is difficult to define beyond an individual level; therefore, it is difficult to measure. The majority of SCA cases are caused by ventricular tachyarrhythmia. Arrhythmic death was reduced thanks to the use of internal cardioverter-defibrillators (Gräsner et al., 2021). With severe heart failure, however, the prevalence of pulseless electrical activity is rising. In patients who are at high risk for SCD, medicines that target the sympathetic nervous system are frequently used to prevent it. Death due to arrhythmia was countered by death due to heart failure (Aune et al., 2018). It is worth noting that younger individuals are classified as shockable or non-shockable (Schluep et al., 2018). The rate of survival from non-shockable rhythms is relatively low, with an increasing proportion of pulseless electrical activity and asystole (Chen et al., 2018). This underlines the significance of public education to respond quickly when warning signs appear. SCA's survival and functional outcome are also reliant on treatment procedures.

7 CONCLUSION

Around 70% of the population had coronary thrombosis. Whereas acute infarction affects more than half of deaths. Until recently, sudden cardiac arrest and death had been observed and tracked. The most common cause of fibrous cap rupture, however, was thrombotic coronary artery disease. According to biochemical analyses, the major causes are smoking, high cholesterol, and glucose intolerance. The left coronary artery is the most commonly affected. As a result, it is critical to raise awareness about the prevention of these causes. "Prevention is better than cure," as the saying goes. A healthy and prosperous society must be established. The term "quality of life" refers to a person's overall health and well-being. This has to be monitored regularly, especially structured heart diseases are abnormalities or issues that happen to the heart leading to health problems.

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Chapter 2
A Review on IoT-Driven Technologies for Heart Disease Diagnosis and Prediction

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ABSTRACT

People around the world are at risk from chronic diseases like cancer, heart disease, and diabetes. When it comes to sudden cardiac arrest, many people have recently become increasingly concerned. The main cause of death in the world is heart disease. Because it needs both experience and advanced knowledge, predicting heart disease is a difficult assignment. Sensor values are being collected for heart disease detection and prediction using internet of things (IoT), which has recently been implemented in healthcare systems. In order to achieve a continuous remote cardiac monitoring system, IoT and wireless technology have advanced significantly over the past several years. The use of various sensors, such as electrocardiograms (ECGs), thermometers, and blood pressure monitors to collect important body signals and diagnose illnesses has resulted in the creation of a wireless body area network. The diagnosis of cardiac disease findings is low in accuracy. The goal is to highlight IoT-driven technologies that have been used in the literature for diagnosing and forecasting heart disease.

INTRODUCTION

Humans have become accustomed to the Internet of Things (IoT), which is employed in a wide range of industries, including education, finance, and social networking. New technologies are being adopted by the healthcare business in order to provide smarter and better healthcare facilities (Y. E. Gelogo et al., 2015). Remote and real-time patient monitoring is now possible thanks to the Internet of Things (IoT). This enables doctors to monitor patients' health in real-time and provides them with the information

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they need to provide appropriate treatment or advice. In order to save lives and promote a healthy way of life for the general population, early detection of heart disease is critical given the enormous number of people who suffer from it. The ability to follow a patient's health status on a regular basis has improved dramatically because of the development of various IoT capabilities and instruments (H. Mora et al., 2017). Patients are also able to communicate with their doctor more readily, resulting in a higher level of satisfaction and a reduced hospital stay and healthcare costs. Utilizing IoT in healthcare is primarily focused on creating a completely automated environment for patient monitoring and real-time care. Portable ECG systems that can be used by patients at home to measure their ECG profiles and diagnose their illness in real-time are becoming increasingly popular. As a result, a thorough examination of currently available technologies for monitoring heart-related disorders is conducted in this work. The raw data has been analyzed and found to include a lot of noise and irrelevant information. Inaccurate and irrelevant facts are not useful in determining the cause of the problem. The classification accuracy, sensitivity, and precision are reduced as a result of the high level of noise and volatility in data. A unique pre-processing method is utilized in this research to remove noise and unrelated data from ECG signals.

The correlation approach is used to identify the most important qualities in order to increase data efficiency. ECG waveforms are used to classify ECG signals using machine learning algorithms such as KNN, naive Bayes, and Decision Tree. Using the classifier with the best performance metrics can help diagnose ECG waveform fluctuation and identify abnormalities and diseases. The rest of the paper follows this pattern. Heart disease and IoT are discussed in Section 2, while Section 3 focuses on related research. Surveyed Techniques are explained in Section 4. The conclusion is presented in section 5.

BACKGROUND

A person's quality of life is severely affected if they have cardiac difficulties. The broad deployment of cutting-edge technology can enhance healthcare systems. The invention of a smart wearable IoT health monitoring device is revolutionizing our lives (ITU-T, 2012). Medical services have made great development in recent years. Technology advancements will allow for a larger choice of services to be provided to patients. As a result of this progress, the quality of life of a substantial segment of the people will increase. Wearable IoT devices allow patients to monitor and regulate their health parameters more effectively. Patients may be alerted about their status at any moment, which is a benefit of these gadgets. To save a patient's life or treat a patient's condition in an emergency, medical professionals can utilize this information. One of the most promising uses of new technology is in the field of connected health. Connected healthcare systems and smart embedded IoT devices may help both businesses and individuals. As a result of this research, it is hoped that linked health systems may be developed that can better inform patients on the state of their health and offer them early medical warnings. It is the goal of the Internet of Things (IoT) to link anything and everyone, everywhere, at any time, via any method, network, or service (O. Vermesan and P. Friess, 2013; R. Clarke, 2013). This objective necessitates further work in a variety of areas, including communication and software. Many research and development organizations are involved in the process. In other terms, the Internet of Everything (IoE) is a network of computers and gadgets of all shapes and sizes that communicate and share information in networks of connections, as defined by Cisco (D. Evans, n.d.).

Cisco predicts that by 2020, there will be 50 billion Internet-connected gadgets. As a metaphor, the Internet of Things (IoT) is a web of webs. There is a separate IEEE standard being created for the IoT's architecture: IEEE P2413 (IEEE Standards Association). People and physical items are networked via ICT and smart networking, pervasive data collecting as well as predictive analytics and optimization in the Internet of Things (IoT) to develop, run and govern the physical world (IEEE Standards Association (IEEE-SA). For the applicable systems, the Internet of Things (IoT) standard provides a reference model, architectural building blocks, and procedures. Internet growth is aided by the global deployment of IPv6 (IETF, Internet Protocol Version 6 (IPv6) 1998), which supports the universal addressing of any "smart thing" that communicates. It will provide users access to billions of connected devices, opening up new possibilities for the Internet of Things. There will be increased demands placed on network functions, management, and composition with the growth of the network itself. IPv6 is required to connect diverse IoT devices and heterogeneous applications in a single network. Low Power Wireless Personal Area Networks (LPWPAN) use 6LoWPAN (B. Djamaa and R.Witty, 2013) as an improved version of IPv6. IoT devices with limited resources implement IPv6.

There is a pressing need to secure the ever-increasing number of interconnected devices in the Internet of Things (IoT). IoT devices must, for example, only provide information to those who have been granted access by the appropriate authorities (J. Penney, 2016). There are several research challenges in IoT hardware development because of the proliferation of small, battery-powered devices. IoT sensors must also be connected to the Internet via communication protocols in order to function. When sensors are put in remote places, the battery life of the sensors must be taken into consideration.

In order to accommodate IoT devices' need for low power consumption, numerous protocols have been established and will be developed in the near future. For example, an effective protocol for IP-based ubiquitous sensor networks for service announcement and discovery has been proposed (B. Djamaa and R.Witty, 2013). Ensuring optimal acquisition speeds, low energy consumption, and little produced overhead while responding quickly to topology changes is the goal of the protocol's fully distributed method for mobile networks, the protocol is able to achieve ideal acquisition times while consuming minimal energy and generating unnecessary overhead.

The Constrained Application Protocol (CoAP), which makes it possible for low-power devices to be seamlessly integrated into the Internet, has been standardized by the Internet Engineering Task Force (Internet Engineering Task Force (IETF)). On most devices that accept UDP, you can run CoAP (P. Sethi and S. R. Sarangi, 2017; P. P. Pereira et al., 2014; H. Khattak et al., 2014; M. Kovatsch, 2013; IETF, 2012). This protocol is a prominent issue in the field of network architecture. Different protocols (Bluetooth, Zigbee, etc.) and networks are used by IoT devices (LANs; WANs). As a result, a platform for the Internet of Things consists of three components: The Internet of Things (IoT) relies on cloud computing as an enabling platform to connect a huge number of devices and sensors. Cloud computing platforms can be used by IoT-based healthcare applications to facilitate sensor communication, rather than building separate mechanisms for all sensors to communicate.

RELATED WORK

It is possible to identify a user's cardiac problems through several research programs, however many of them lack essential components. Companies have capitalized on the influx of eHealth research being conducted by individuals and have developed platforms that link patients with doctors all around the world.

Arm-band ECG (V. P. Rachim; W. Y. Chung, 2016) recommendations are built with a variety of features in mind. A Bluetooth low energy (BLE) data transfer and an Android mobile application are included. Timely heart rate detection was included in the software for Android applications that were tested in a variety of circumstances, from lying in bed to exercising in place or running while standing up. According to the findings, this type of monitoring is effective in each of these scenarios.

Ufoaroh et al. (2015) primary goal is to develop a wireless sensor network system that can continuously scan and identify cardiovascular illness in patients in far-flung locations. In order to monitor the patient's ECG, a wearable wi-fi sensor system (WWSS) was developed. Using the suggested data processing method integrated with the patient's cell phone, the fastest notice will be given to physicians, families, and hospital wards. In order to solve this issue, a Bluetooth (BT)-based wireless network might be built to record, monitor (M. Bhoyar et al., 2016), and analyze ECG data (ECG). Following the established positions of Einthoven's triangle, three surface electrodes are implanted on the chest. The signals measured are amplified and filtered before being sent to the Arduino UNO board. ECG data is sent from Arduino UNO to a mobile device via Bluetooth, where it may be analyzed by a medical professional at a workstation (Peter Leijdekkers, Valérie Gay, 2018) introduces a wearable cardiac monitor for real-time monitoring of a user's heart rate.

Researchers from the University of Technology, Sydney's Peter Leijdekkers et al. (2018) have developed an individual trial application that shortens delays in reporting heart attacks to the emergency services. A cellular device and a tiny ECG sensor, which may be worn and efficiently conveyed by the user, are used in the individual test to understand these problems. The person admits that what they went undergone was a heart attack by looking for a set of questions. In addition, the program examines two ECG records on the cell phone for signs of a heart attack. Without the intervention of a therapeutic specialist, an application can quickly assess a client's situation and provide required advice. Using computerized call routing also guides customers and viewers to the appropriate resources. A 2-terminal, 1-lead cardiac monitor records and analyses the ECG in real-time on the mobile device. In this case, ventricular tachycardia may be detected using the method used. If the program determines that the user is in danger, it prompts the user to notify the appropriate administrator as soon as possible to prevent further damage. In the event that a user experiences a heart attack, the system automatically determines the user's present position and alerts the appropriate medical personnel.

A.A.Gurjar et al. (2018) devised a system for monitoring heartbeats and logging the site of heart attacks. An Internet-connected microcontroller reads pulses from the sensor and transmits them. The user has the ability to control the maximum and minimum heart rate. At a later stage, the monitoring will verify whether or not the heartbeats are going beyond or below the set limits. The patient's transmitting circuit and the authorized personnel's transmitting circuit are employed. The LCD panel displays the current pulse rate as a result of a heartbeat sensor. There are no limitations on where this technology may be used. Using the gadget doesn't require you to stay at home and stay there.

Nikunj Patel et al. (2018) developed a system for detecting a heart attack by monitoring the pulse, which is dependent on the item's web. A heartbeat sensor, an Arduino board, and a Wi-Fi module are used in our method. After setting up the framework, the beat sensor will begin detecting pulse readings and will display the heartbeat of someone on the LCD. In the same way, information may be transmitted via the web by utilizing a Wi-Fi module. The framework gives a reference point that may be used to determine whether or not an individual is healthy by comparing their pulse to the set point. It will begin monitoring the patient's pulse when these limitations are set and will send an alert message as soon as the patient's pulse rises or falls as far as possible. As part of this effort, we're putting together an Android app that will monitor a patient's heartbeat, screen it, and then provide a crisis warning about the likelihood of a heart attack.

Researchers from KVCET in Chennai, Tamil Nadu, India, K.S.Abbirame et al. (2018), proposed a developing framework that might lower the death rate from heart attacks by locating them earlier in the process. We use pulse sensors, GSM, and GPS in our framework to accurately measure the pulse and provide the corresponding data. The customer's pulse will be continuously monitored by the pulse sensor. We have made the advantage a reward in the framework. As soon as it falls below or rises over a certain threshold, a microcontroller will activate GSM and GPS so that information may be exchanged with the nearest health department and with the client's family members. When a client's pulse becomes too high, the structure will send a message to the nearest wellness center and the recently deceased relative's phone number.

Using a micro-scale controller and a heartbeat sensor, A. Dutta et al. (2017) of the Institute of Engineering and Management, Salt Lake, Kolkata, have developed an innovative Gadget. It identifies the beat rate and shows the illness that is suggested by the pulse example. Before using the machine, the user must first select his age and sexual orientation. The patient's condition is relayed to the patient through the microscale controller's presentation and alert section. Understanding the necessity for any crisis medication or a consultation with a professional is an added benefit. In addition, arrangements will be made to show customers their most extreme employees so that they may push their limits in order to live a healthy lifestyle. The gadget is in use for 24 hours, and all captured data is still available for review. Rather than relying on doctors, the customer may discover the true state of his heart's workings on his own. The development of bio-electro cooperative ventures has been aided by the development of this device. This is a wired device that may be further enhanced by the addition of a remote element. It is possible to supply or attach a direct specialized video connection to it. It is possible that a connection to Wi-Fi for smart devices can be established there. This gadget can not only regulate (to some extent) serious cardiac problems that affect every family, but it can also provide motivation for increasing one's working capacity by exhibiting the individual the intensity of one's pulse. There are many people who die before they reach the clinics since they can't be given the main regulating medicine that can handle their situation for an extended period of time because of this device.

Researchers from Abu Dhabi University, UAE (Samr Ali, 2017), have proposed a system that uses heart attacks to detect automobile collisions and the negative implications they may have on drivers. It was revealed that the administration's IoT-enabled system and two versions were on display. They demonstrated a mobile heart attack detection service that was voice-activated, as well as a motion-controlled display. Both utilize sensors from smart, which has gained notoriety amongst customers and increased accessibility. The basic type of real-time mobile heart detection system only considers how the client can use administration in cars, whereas the second type helps the client outside of vehicles. On top of that, they talked about and demonstrated how the system works, as well as the underlying technology it employs. Using FDA-approved ECG sensors embedded in wearable electronics, they also hoped to test if an attack on the heart might be detected by the software.

Protective evaluation procedures for the driver and the vehicle were upgraded by Pughazendi N et al. (2017). Sensors should be used, according to the study. A heartbeat sensor is used to monitor the driver's heartbeat every 60 seconds and prevent accidents by controlling it over the internet. The crisis notice is sent on to the proper authorities since the Internet is connected to a wide range of devices. Driving rules and guidelines are taken into consideration while using traffic light sensors. If the red light is on, the vehicle will come to a halt before it reaches the prescribed fixed line if the light is on. In the case that the vehicle's fuel supply is insufficient to reach its destination, a guide will tell the driver that a nearby gas station is the best option, and the driver will be urged to do so.

In the accompanying paper, Arulananth T.S et al. (2017) stated that the ECG waveform or the user's pulse may be used to identify heart rate. It is constrained by the heart's regular withdrawals to keep a supply route of blood from developing and withdrawing at a regular pace. When the course is near the skin, the beat may be felt. An Arduino microcontroller and the tip of a finger are used to depict a way of computing the pulse. A light source and an indicator are used to calculate the blood volume variation in tissue using Photo-Plethysmography, a non-invasive approach. The blood volume in the finger course changes as the heart pumps blood across the body, causing the blood volume in the finger to change as well. An optical sensor encircling the fingertip can pick up on the blood's pulsation. Sequential port communication is used to transmit the increasing flag to Arduino. As a result of planning and programming, pulse monitoring and counting may be done effectively.

Heart attack prediction systems, according to D. Selvathi et al. (2017), do not exist and patients are only followed after they have had a heart attack. Heart attacks can be detected by counting the number of beats per minute (bpm) that a patient's heart is making. When a heart rate exceeds the normal range (60-90), it's taken as a sign of an impending heart attack. The heart rate signals are picked up by a heartbeat sensor, which is used. Accumulated findings are verified by the microcontroller. A mobile communicative module is activated by the microcontroller when the beats are more or less prominent than specified dimensions, and an alert indication is sent to important contacts recorded in an MCU. Both sexes are taken into consideration when testing the framework.

By analyzing ECGs and other medical records, Ponugamatla Kalyan et al. (2017) were able to accurately predict the prognosis of heart disease. A heart-monitoring system using Arduino and Raspberry Pi 3 is shown in this study. The Arduino board is connected to an AD8232 heart rate sensor module, and the Arduino board interacts serially with the Raspberry Pi board. In order to conduct a USB to UART function between the raspberry pi and GPS, the NEO6MV2 GPS module is connected to a PL2303 USB to TTL converter We utilized python to run the entire system and save all the sensor data in the cloud using HTML and Wi-Fi, and the software sketch we used here. All sensor data may be accessed through the internet or a mobile phone, and the subject's heart health can be monitored at any time and from any location. Patients can benefit greatly from this design system that creates changes in their health, if necessary. It is imperative that we notify the relevant doctor or the referring physician immediately of any changes in the medication, location, etc.

Sensors that may be worn and gadgets like mobile phones can assist keep a record of the user, according to Lei Song et al. (2015) of the Institute of Interdisciplinary Information Sciences. It keeps track of the body's current conditions and delivers or stores the results to loved ones or specialists who aren't close by. So, it may help people pay attention to the little things, such as a warning sign of an unsafe sickness, or it can assist them to give an alarm when a crisis occurs. It was found that using body sensor systems and mobile phones, researchers were able to elicit the most inventive and advantageous conditions from even the toughest and most challenging situations. Each subarea's growth lines are also aided by a rundown as well as an assessment of the related detecting systems and computations.

Continuous remote monitoring of the heartbeat is offered by Ufoaroh SU and co-workers (2015) in a system that includes improved caution and SMS alerts. The goal of this project is to provide a low-effort but highly effective and scalable heartbeat monitoring and ready framework that utilizes GSM technology. If the maximum heart rate limit is exceeded, an alarm and SMS will be sent to the restorative master's mobile phone, and the system will continue to monitor and warn them. The system is designed to detect and analyze the heart rate using sensors and display the findings on an LCD.

In order to track patients with heart failure, Abdel-Basset et al. (2019) used an IoT and computer-supported diagnostic system. Initially, the data from the body sensors concerning heart failure symptoms was acquired by the users' mobiles using Bluetooth technology and sent to the cloud database via a smart gateway. Patients were separated into a number of groups based on the symptoms they presented with. An integrated IoT and NMCDM approach was used to identify, monitor, and control cardiac failures at a low cost and in a short period of time with little time and resources required for analysis. Experienced outcomes verified the high-level system's ability to function at its best.

For processing and storing large amounts of wearable sensor data, Kumar and Gandhi (2018) advocated a scalable three-tier architecture. It was Tier 1's job to gather the data from the wearable sensors and put it together. The wearable IoT sensor data is successfully stored in a cloud computing environment using Apache HBase. In Tier 3, Apache Mahout was used to building the heart disease prediction framework using logistic regression. Finally, a receiver operating characteristic (ROC) analysis was used to identify the most important clinical characteristics of heart disease. Cloud and IoT-based mobile healthcare applications were recommended by Kumar et al. (2018) for monitoring and diagnosing severe diseases. Among the system's components are medical IoT devices, medical records from the University of California Irvine (UCI), a data collection module, a cloud database, a protected storage mechanism, a knowledge base, and a health prediction and diagnosis structure. Health conditions may be estimated using a fuzzy temporal neural classifier in this system. It was shown that this strategy beats other approaches in terms of actual results.

Automated diagnostic systems for the cardiac disease have been proposed by Ali et al (2019). Feature vectors were first normalized, and then the data were split up into training and testing collections. A statistical framework was then used to pick and rank the training data. The framework used the same subset of attributes that it selected for training in order to test the data. A neural network (NN) used training data with a smaller number of variables for training purposes. The test data was used to evaluate the trained neural network's performance.

Gupta et al. (2017) proposed an IoT-based cloud infrastructure. Instead of using smartphone sensors or wearable sensors to capture the values of fundamental health-related measures, the revealed technique made use of the equipment's built-in sensors. Public and private clouds are all components of the new architecture based on the internet of things (IoT). Data was quickly and securely sent via XML Web services in this design. The general response time between the CDC and the local database server stayed practically constant as the number of users grew. This was evident.

Using a blockchain-based healthcare architecture, Rathee et al. (2019) proposed a secure healthcare system. It was used to ensure the security and accessibility of documents, healthcare information, and the shipping process between providers and customers. Using the framework's experience analysis, hostile IoT objects committed illegal behaviors or communicated with one another. Weights can be identified using a population diversity and tuning tool provided by Vijayashree and Sultana (2018). A fitness function for particle swarm optimizations (PSO) using support vector machines was also built by the offered system (SVMs).

Sex, maximum heart rate, fasting blood sugar level, resting ECG, multiple primary vessels, and exercise-induced angina were all discovered using the PSO-SVM feature selection method. PSO-SVM was compared to other contemporary techniques in terms of performance. Methods recommended by the author were shown to be more effective than other options. Three key elements were identified by Mutlag et al. (2019) load balancing, interoperability, and compute offloading, which were used to address potential and current resource management issues in healthcare IoT systems. The RFRS feature selection method and a classification system with an ensemble classifier are both proposed by Liu et al. (2017). A heuristic rough set reduction strategy that we designed reduces the number of features using the Relief FS technique. This algorithm is then used to reduce the number of features in the final model. Ensemble classifiers based on the C4.5 classifier are proposed in the second system. The UCI database's Statlog (Heart) dataset was used in the tests.

Using a heart illness dataset, Haq et al. (2018) developed a machine-learning-based diagnostic technique for heart disease prediction. In all, they used seven popular machine learning algorithms, three feature selection approaches, the cross-validation method, and seven classifier performance assessment parameters such as classification accuracy, specificity, sensitivity, Matthews' correlation coefficient, and execution time. People with cardiac disease can be easily identified and distinguished from healthy individuals using the described technique. Hybrid machine learning can be used to predict cardiovascular disease, according to Mohan et al. (2019). There is a model called HRFLM, which is a hybrid random forest with a liner model.

There are several layers in the traditional Neural Network that are used to learn lower and higher-level characteristics. A new approach, called layer-wise preparation, was devised in 2006 by Hinton and Salakhutdinov (2006) for training the deep-design neuron layers. When a deep network is trained layer by layer, this calculation is viewed as a single layer avariciously prepared. Many deep network systems are now being prepared using this method since it has been shown to be more effective in the long run. Using convolution and subsampling, the convolutional neural system is one of the most often used deep systems for extracting the modest to substantial levels of highlights from features that are hidden behind several veiled layers. Incredible productivity has been predicted for this system in a variety of areas including, but not limited to: computer vision, organic computation, distinguishing mark enhancement, and more. These systems are made up of three layers: convolution layers, subsampling or pooling levels, and complete association levels. The fusion of a memory cell allows LSTM to modify long-term circumstances by saving the state after a period of time. In LSTM, three gates are used to determine which data should be highlighted or ignored before the next subsequence is started. LSTM has proven useful in a variety of contexts, including machine interpretation, speech recognition, and image subtitling, among others. There have been various attempts to use LSTM for clinical prediction based on electronic health information in the restorative field. Using a lightweight authentication scheme, Zouka and Hosni (2019) were able to protect sensitive patient data while still maintaining a reliable connection. Using an M2M patient monitoring screen and a remote health app, the recommended structure allows doctors to keep track of patients' biosignals in real-time. The findings confirmed that the recommended structure yielded high-level results by reducing the access time overhead. In terms of both verification and transfer times, the structure takes longer to generate a key.

SURVEYED TECHNIQUES

A. Detection of Heartbeats

Fingertip pulses are picked up by a heartbeat sensor and used to calculate the heart rate. It's the heart's job to pump blood into the fingertip's artery as it beats. A change in blood volume is caused as a result of this activity, and the heartbeat sensor records this change. An infrared light source and a photon detector are located on the finger's two sides, with the photon detector being used to monitor changes in blood flow. In this procedure, a PPG waveform is detected. In time with the heartbeat, we see this PPG waveform. As a precaution, the patient's heartbeat is recorded and monitored. The optimal heart rate range is between 60 and 110 beats per minute. A heart attack is more likely if your heart rate is higher or lower than this. The microcontroller communicates with these values.

B. Interfacing Sensors

For example, the microcontroller processes a beat from a sensor module and calculates a pulse before sending this information to the liquid crystal display. It acts as an interface between the sensor and the data it collects.

C. Connecting to the Internet using Wi-Fi

This module sends an alarm message to the doctor/nurse and the patient's/distant user's family in the event of an irregular heartbeat reading.

INTEGRATION OF IOT WITH MACHINE LEARNING

The traditional healthcare system must be improved and upgraded due to the increasing number of patients in their middle and senior years who suffer from chronic and heart-related ailments. In most cases, heart illness is the only reason people go to the hospital. Patients must travel to the hospital to have their cardiac conditions checked and their physiology of the heart studied in the typical ECG setting. The patient's movements are restricted throughout this time. The cost of medical care rises as a result of frequent visits to the hospital. Building an automated system to detect aberrant heart signals has received a lot of interest and effort because early intervention is critical to patient survival. IoT wearables were designed to measure ECG signals (Z. Yang et al. 2016). The patient's ECG readings are collected by a non-invasive wearable sensor and sent to the IoT cloud using Bluetooth or ZigBee technology via a smartphone. The professional can access the cloud-based data and use data analytics to look for the ailment. Having access to a remote server can be used to perform the data analytics method of cleaning, storing, analyzing, and sending warning warnings to the concerned professional in real-time. Machine learning techniques are being used to make it easier to detect cardiac problems at an early stage. The aberrant functions of the heart were studied using the health dataset. SVM, Adaboost, ANN, and Naive Bayes classification algorithms were used to assess the amplitude and interval periods of the cardiac waves to classify the data (S. Celin and K. Vasanth, 2018). A physician's ability to make fast and accurate diagnoses and treatments will improve if classifiers can be identified. Heart rhythm problems are associated with several types of arrhythmic illnesses. The extraction of statistical and dynamic information from ECG data is essential for appropriate diagnosis (R. L. D. V Kalaivani, 2019). Because of the arrhythmia disorder that the patient has, heart rate variability is used to create alarms. In (M. Hammad et al., 2018), a novel classifier was presented to discriminate between a normal and pathological heartbeat rhythm to simplify the time-consuming procedure of manually examining the ECG data. ECG features can be extracted once the noise has been removed using this classifier. When compared to other machine learning classification techniques, our classifier performed better. Arrhythmia disease can be diagnosed more easily because the time computation is lowered. A patient's chance of survival is greatly increased when irregular pulse rates are discovered early. The automatic identification of cardiac arrest was therefore proposed in order o enhance survival rates. The random forest classifier (RF) is used in the ECG-based pulse detection system (Elola et al., 2018). The ECG data were processed to reduce background noise and extract the most important information. When comparing random forest classifiers to existing classifiers, the features were compared to the random forest classifier. The improved performance of the RF classifier aids practitioners in making quick treatment decisions. Data cleansing, data transformation, data integration, and data reduction are all common applications for pre-processing (W. S. Bhaya, 2017). The data is cleaned by identifying missing values, removing noise, and identifying outliers. Cleaning the data significantly improves the classifier's performance. There are a variety of pre-processing methods that can be used to enhance the dataset's performance metrics. The preprocessing aids the classifier's performance, as can be deduced from (C. Zhu, 2016). An outlier-based alert system was utilized by (M. Hauskrecht et al., 2013) to discover patient anomaly data and reduce measurement mistakes. The system worked well when it was tested in a real-time environment. Classifying ECG data is proposed in the following section using unique pre-processing techniques.

CONCLUSION

IoT and wireless technologies have improved greatly over the past few years in order to develop a continuous remote cardiac monitoring system. To collect vital body signals and identify ailments, a wireless body area network has been created by utilizing a variety of sensors, such as an electrocardiogram (ECG) and temperature devices. There has been a lot of research on the diagnosis of heart illness, however, the results have been low inaccuracy. When a patient is placed in a distant area where there are no medical services, monitoring and prediction systems can assist save many lives by providing immediate care. It is difficult to determine how long a person will live with heart disease. All of the IoT-based cardiac disease detection and prediction strategies that have been proposed in the literature have been covered in this chapter.

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Chapter 3
Leveraging AI Technologies for Preventing and Detecting Sudden Cardiac Arrest and Death

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ABSTRACT

AI is used for alerting people who are suffering from heart problems. The patient's language, sound, accent, voice, and other patterns are analyzed in an audio call for heart problems. The CPR and defibrillation treatment is used. Delay in sudden cardiac arrest can create problems in the brain, and fatal implications might be there. Biosensors are recommended for heart patients, and they can be worn on the wrist to detect hypertrophic cardiomyopathy. This condition or disease occurs because of cardiac muscle thickening. This is the reason for heart failure, stroke, and fatality in heart patients. The other observation is outflow tract obstruction in the heart patients who had sudden cardiac deaths. This happens in patients who have high blood pressure and can be identified using blood pressure and echocardiography instruments.

By augmenting human performance, AI has the potential to markedly improve productivity, efficiency, workflow, accuracy, and speed, both for [physicians] and for patients … What I'm most excited about is using the future to bring back the past: to restore the care in healthcare." — Eric Topol, MD, director and founder of Scripps Research Translational Institute

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INTRODUCTION

AI is used for alerting people who are suffering from heart problems. The patient's language, sound, ascent, voice, and other patterns are used to analyze an audio call for analyzing the heart patient's problems. CPR and defibrillation treatment are used. Delay in sudden cardiac arrest can create problems in the brain, and fatal implications might be there. Biosensors are recommended for heart patients, and they can wear on the wrist to detect hypertrophic cardiomyopathy. The biosensor helps in identifying Hypertrophic cardiomyopathy in heart patients. This condition or disease occurs because of cardiac muscle thickening. This is the reason for heart failure, stroke, and fatality in heart patients. The other observation is outflow tract obstruction in the heart patients who had sudden cardiac deaths. This happens in patients who have blood pressure and can be identified using blood pressure and echocardiography instruments.

As we all know, the heart is our body organ. The heart helps in pushing blood to our body after the oxygenation of the blood. Sudden cardiac arrest happens due to the heart not working.

It is due to electrical disturbance, which creates abnormal heartbeats. The heart stops pumping blood due to this abnormality. Human goes unconscious and it might result in death if ignored for more than 5 minutes.

Note: Sudden cardiac arrest happens to a patient with no alarm or a signal. It happens because of an electrical problem in the heart, which creates an abnormal heartbeat. The blood pushing stops and the heart can push the blood to the other organs, such as the lungs and brain.

The symptoms before sudden cardiac arrest happen to a human being:

- Sudden collapse
- Loss of consciousness
- Loss of breathing
- No heartbeat
- Difficulty in breathing
- Feeling dizzy
- Chest pain
- Nausea
- vomiting

Let us now look at the difference between sudden cardiac arrest, heart attack, and stroke.

Table 1 shows the difference between sudden cardiac arrest, heart attack, and stroke.

Table 1. Difference between SCA and heart attack

Health Condition	SCA	Heart Attack	Stroke
Attention	Unresponsive	Responsive	Normal
Breathing	abnormal breathing	breathing	poor blood flow or hemorrhage
Heart Beat	heart stopped	heart beating	Normal
Immediate external application	Needs CPR/AED	does not need CPR /AED	Normal
Cause	triggered by a problem with the heart's electrical impulses	occurs when blood supply stops,	Normal
Walking	Normal	Normal	inability to walk
Mental state (David D. Luxton 2015)	Normal	Normal	mental confused
physical condition	Normal	Normal	sudden weakness on one side of the body
Speech	Normal	Normal	disrupted speech

CPR is a procedure for treating sudden cardiac arrest. Let us see how it works.

How It Works - CPR

1. The patient needs to keep the back to the surface and sleep
2. you need to place your hand on the top of the heart of the patient
3. Fingers need to be locked
4. The chest needs to be pressed again and again
5. The airway can be opened and breaths can be provided
6. Chest needs to fall
7. If not, repeat chest pressing and provide breathes

Let us now look at different causes of sudden cardiac arrest. The electrical disturbance is a major reason. Heart rhythm becomes irregular and causes ventricular fibrillation or ventricular tachycardia. Electrical abnormalities like Wolff Parkinson White Syndrome and Log QT Syndrome can cause sudden cardiac arrest for children and young patients.

The other reason for cardiac arrest is heart rhythm speed decrease referred to as bradycardia. Abnormal heartbeats might cause life-threatening arrhythmias. Heart tissue scarring can also cause life-threatening arrhythmias. Six months before a heart attack is a time when a sudden cardiac arrest can happen to atherosclerotic heart patients. Heart muscle problems can cause heart valve disease, blood pressure, and other problems. This is referred to as cardiomyopathy. Sudden cardiac arrest can happen due to cardiomyopathy. Heart medications for arrhythmias treatment can cause ventricular arrhythmias. This is called the proarrhythmic effect. This can be due to blood level changes in magnesium and potassium.

Recreational medicines can be one of the reasons for sudden cardiac arrest in healthy persons. The other reason can be blood vessel irregularity, especially in the aorta/coronary arteries. Intense physical exercise can trigger heart arrest because of the adrenaline released.

Sudden cardiac arrest can cause mild, severe, and life-threatening conditions. It can cause the following conditions:

- Heart complications
- Neurological complications

Patients with the following heart problems can have cardiac arrest:

- Coronary Artery Disease
- Irregular Heart Valves
- Heart Arrhythmia
- Electrical Impulse Problems
- Previous Episode of Heart Attack

The risk factors which impact sudden cardiac arrest are:

- Age
- Family History
- Stress
- Electrolyte disturbance

The electrolytes which can cause problems due to disturbance levels are:

- potassium
- calcium
- magnesium

Now let us look at the immediate treatments available for Sudden cardiac arrest:

- Cardiopulmonary resuscitation (CPR)
- Defibrillation

Long-term treatments for this condition are:

- Antiarrhythmic drugs
- Beta-Blockers
- Calcium channel blockers
- Angiotensin-converting enzyme (ACE) inhibitors
- Coronary Angioplasty
- bypass surgery
- Corrective Heart Surgery

To avoid heart problems, you can follow the below recommendations:

- avoid smoking and not take alcohol
- manage your stress levels
- have a good and healthy diet
- avoid sedentary lifestyle
- perform regular exercise
- ensure you control your weight
- have a good sleep
- you can have regular health check-ups

After recovering from this condition, patients might have mild chest pain and mood swings.

SUDDEN CARDIAC ARREST DETECTION

Sudden Cardiac Death happens because of Sudden Cardiac Arrest (SCA). The heart stops functioning, and the heartbeat goes to zero in the heart patients when SCA occurs. The other organs stop working because of the restricted blood flow when SCD happens. Attention from medical experts needs to happen in minutes to help the patients when SCA happens. In nine minutes, a patient needs to be treated for brain damage. Resuscitation of the patient can cause comatose and brain damage condition.

The symptoms related to SCA are vomiting, shortness of breath, chest pain, and others. Coronary artery disease can be a root cause of SCA and SCD. 80% of the heart patients who had coronary artery conditions resulted in fatalities. The others end up with Cardiomyopathy and genetic channelopathy. The other reasons are obesity, alcohol habits, and fibrosis. The other condition called arrhythmias is the cause of cardiac arrest. This condition happens because of heart rhythms which are not common. Ventricular fibrillation is another reason for SCD. SCD results in the brain, lungs, and organs not functioning. It starts as a malfunction in the heart, creating an uncommon heartbeat.

Now let us look at the method to detect and prevent sudden cardiac arrest.

PHOTOPLETHYSMOGRAPHY

Photoplethysmography is a popular technique that can identify blood circulation changes in a non-invasive way. Oximeters and smartwatches can identify heart rates. PPG technique blended with classification technique helps in detecting hypertrophic cardiomyopathy in heart patients. Health care organizations create chatbots and conversational AI (Adam Bohr and Kaveh Memarzadeh 2020) assistants for spreading awareness to patients who have heart problems. NLP & NLU techniques are used to understand the patient's condition to provide guidance and tips.

Note: Photoplethysmography (PPG) is a technique that is non-invasive optical to identify the blood content changes in the skin.

350k SCA cases happen every year outside the hospital and the fatality rate is greater than 88%. CPR helps in improving the recovery from SCA. Two weeks before SCA, the patient gets chest pain or breath shortness. Patients might have dizziness, fainting condition, fatigue, and a higher heart rate. The other conditions observed are uncommon heartbeats, heart palpitations, light-headedness, wheezing, and discomfort in the chest. There is a higher chance of men getting SCA compared to women. The other observation is that SCA patients had diabetes, high blood pressure, heart failure, chronic kidney disease, higher cholesterol levels, and inflammations.

Nearly 25% of heart patients have died after SCA. Around 18% of 70-year-old heart patients survived for 7 years after SCA. In the age group of 18 to 69 years, the fatality rate was 55%. The risk of SCA is lesser among young adults. In young athletes, the risk is higher during fitness programs or sleep.

HEART RATE VARIABILITY

Heart Rate Variability is another technique used in classifying heart defects in patients. Heartbeats are analyzed for ectopic beats removal. They transformed using discrete wavelets and mean wavelets. Distinct features are identified for SCA prediction by processing Heart Rate Variability in time. It helps in identifying heart problems like the variation in time between two continuous heartbeat segments. Cardiac health is an important factor for body health as it shows the autonomic nervous system condition. This analysis helps in restoring the body's condition to homeostasis and applying directed activity. We can use the signals for identifying features such as name, time, frequency, and nonlinear domains. SVM and Neural Network techniques are used to analyze the feature vectors for SCA prediction.

Some features used for Neural Network analysis of HRV signals are:

1. Mean of NN interval
2. Max of NN interval
3. Min of NN interval
4. Median NN interval
5. Standard deviation of all NN interval
6. Standard deviation of average NN intervals in all 1-minute segment
7. Number of NN intervals which differ in greater than 50 ms
8. Average Number of NN intervals which differ in greater than 50 ms
9. RMS of advanced NN intervals
10. Mean of Standard deviation of all NN intervals for 1minute segments
11. Mean heart rate
12. standard deviation rate of heart rate
13. HRV triangular index
14. triangular interpolation of NN interval histogram
15. number of ectopic beats

The other factors which can be included in the analysis are:

1. Malignant arrhythmia
2. cardiopulmonary resuscitation
3. rehospitalization because of HF

The patient's background is gathered for profile analysis. The key attributes are:

1. Demographic variables

2. clinical variables
3. biological variables
4. electrophysiological variables
5. sociales variables
6. psychological variables

The databases which are typically used for Machine learning analysis are:

1. MECKI (Metabolic exercise test data combined with cardiac and kidney indexes)

    1. GISSI-HF (Gruppo Italiano per lo Studio della Streptochinasi nell'Infarto Miocardico-Heart failure Trial)
    2. EMPHASIS-HF (the Eplerenone in Mild Patients Hospitalization and Survival Study in Heart Failure trial)
    3. I-PRESERVE
    4. SHFM (the Seattle Heart Failure Model)
    5. HF-ACTION (A Controlled Trial Investigating Outcomes of Exercise TraiNing trial)
    6. CHARM (the Candesartan in Heart Failure: Assessment of Reduction in Mortality and morbidity)
    7. MAGGIC
    8. CVM-HF (CardioVascular Medicine Heart Failure index)
    9. 10.3C-HF
    10. 11.MUSIC (MUerte Subita en Insuficiencia Cardiaca study)
    11. BARDICHE (Body mass index (B), Age (A), Resting systolic blood pressure (R), Dyspnea (D), N-terminal pro-brain natriuretic peptide (NT-proBNP) (I), Cockroft-Gault equation to estimate glomerular filtration rate (C), resting Heart rate (H), and Exercise performance using 6-min walk test (E))

For analysis, patients with the following diseases are not included:

1. Hypertrophic cardiomyopathy.
2. Rheumatic heart disease.
3. Congenital heart disease.
4. d)Pulmonary heart disease.
5. Pericardial diseases and myocarditis.
6. Acute myocardial infarction
7. ST-segment elevated myocardial infarction (STEMI)
8. NSTEMI.
9. Aortic dissection
10. leukemia
11. lymphoma
12. aplastic anemia.
13. Autoimmune disease.
14. Malignant tumor.

15. Hormone replacement.

AI and ML techniques are used for SCA and SCD prediction. The analysis needs to include larger datasets for better prediction.
Let us look at the AI/ML techniques.

AI/ML

Background Feeding of AI

Typically, AI works on the fed large body of data, so it is learning from the collected digital information. The computer or machine learning is exposed to thousands of ECGs that are both normal and weak heart pumps, through sheer recognition it could learn the subtle heart pattern associated with a weak heart pump. Developing new AI tools requires Subject Matter Experts, IT professionals, Health care professionals, Clinicians who understand the disease, Engineers hands-on with Python and the language of machine learning, large carefully curated data sets, and various ECGs with labels to feed the computer the specific ECG is associated with particular cardiac dysfunction. Infrastructure needs to be developed which requires Cloud or In House IT professionals with DevOps and Security operations expertise. Quality Managers with test engineers will be needed to focus on the AI system quality and data quality. Ideally, data management professionals are required for data cleansing and staging. To manage the program, you need program and project managers to execute these AI system implementations in the hospitals.

AI/ML Models

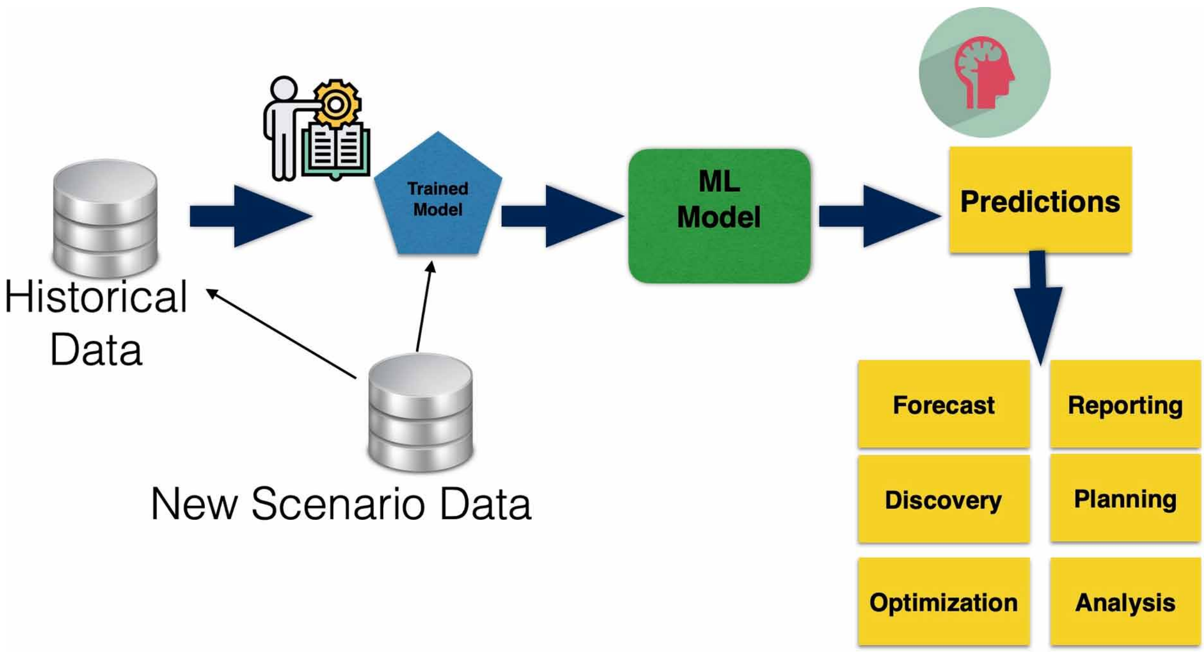
AI and Machine Learning are used for the prediction and prevention of heart problems. You can create analytical models for human heart rates using AI/ML techniques. Heart rate data from patients is used for model learning and a trained model is used for prediction of the heart problems.

AI modeling and development process of creating the human heart rate models consists of:

- Selection of Modeling Techniques for heart rate analysis
- Algorithm Selection for heart rate variability analysis
- Test Data Design for heart rate models
- Human Heart Rate Model Development
- Human heart rate Model Assessment
- Human heart rate Model Training
- Human heart rate Model Validation

Figure 1 below shows the process of AI-ML model development.

Figure 1. AI-ML model development



In the diagram above, the usage of historical and new scenario data is shown. How new scenario data helps in enriching the model in real-time after a cold start. The scenarios where this model can help and the use case are also shown in the diagram above.

Training data sets are created for the Heart rate variability AI model. HRV AI model consists of data that can train the model. Training rules and techniques are implemented to relate input heart rate data with output heart conditions. HRV AI model can be trained by using ML techniques, and 80% of the data is used for training. Testing data sets are created for the HRV AI model. HRV AI models are tested using 20% of the data available. Testing helps in evaluating the precision and accuracy of the Heart rate variability AI model. Heart rate variability historical data sets are gathered for better accuracy and precision. Historical heart rate variability data of the patients can be recorded and publicly available data. These datasets help in creating an accurate HRV AI model for prediction and prevention. These heart rate datasets help in identifying the trends and patterns in human patient rates. Using the trends, you can isolate the abnormal or outliers in the heart rates of the patients. Historical trends help in coming up with solutions for improving the diagnosis of the heart condition and the decision-making.

The ensemble method helps in mixing different approaches based on real-life health situations of the patients. Different ML algorithms are used as AI techniques in the model. The algorithms are listed below:

- Classification
- Regression
- Decision Tree
- Support Vector Machine
- kNN
- k-Means

- Random Forest
- Naive Bayes
- Dimensionality Reduction
- Gradient Boosting

HRV AI models are measured for precision and accuracy using multiple unseen HRV data sets. You can refine the HRV model and measure the precision of the new and unseen HRV datasets. HRV Models are deployed in the testing environment. Test data from the patients is used for validation of the model. In the production environment, these HRV models are tested with new and unseen data sets based on new scenarios.

For unseen scenarios related to heart problems, you can use supervised learning-based algorithms. Training data is used for creating an HRV AI model. You can create a prediction model for live, unseen, offline, and new patient and heart rate data. The heart rate data sets have attributes that are referred to as features. Features are the basis for the HRV prediction model. Test data is used in offline quality assurance and control environments. The production environment helps in assessing the model for new scenarios (Arash Shaban-Nejad et al. 2020).

The feedback which comes from the live HRV model deployment helps in improving the HRV model. The feedback helps in retraining the HRV prediction model. The accuracy and precision improve with the retraining of the heart rate variability model. HRV AI Models are measured for prediction precision using live and unseen data. Precision metrics are based on the known heart condition scenarios and unseen scenario feedback related to heart conditions. The split between validation and training heart rate variability data is around 80-20%. You can measure the HRV AI models in the production and testing environments. You can tune the heart rate variability model parameters by changing the split between the training and validation of heart rate variability data. Splitting types are listed below:

- Random
- Stratified
- Fraction

The tuning parameters are as follows:

- Cold users
- Test users
- Ignored users
- Ignored items
- Validation metrics

You can verify the training model and the prediction using the following metrics:

- False Positives
- False Negatives
- Accuracy
- Precision
- Recall

- The area under the curve
- Receiver Operating Characteristic Curve

  Precision = True Positives /(True Positives + False positives)

  Recall = True Positive /(True Positives + False Negatives)

  AUC = P (Random Positive sample rank > Random Negative Sample)

HRV AI models can help in prediction, forecasting, and pattern identification. Machine learning techniques are applied to identify patterns in heart rates. Using the historical heart rate data of the patients, trends and patterns are identified. Heart rate variability pattern identification is based on previous knowledge and represents the knowledge as patterns and trends. These are based on the features and characteristics of the data. The time series of the recorded heart rate data helps in identifying future trends. The HRV AI model helps in creating pattern classification and clustering. Pattern identification helps in identifying fraud and fake information in the patient's data.

CHATBOT

Chatbots are used for information and knowledge sharing for heart patients. Instead of humans answering the questions, the chatbot can be trained to answer queries from a knowledge base related to sudden cardiac arrest. A chatbot can handle audio and text input, which is recognized for NLP and NLU analysis. NLP and NLU techniques help in analyzing the words and answering the queries related to heart problems from the knowledgeable.

Chatbot helps in gathering the information required for heart problem diagnosis. The information gathered is used for heart problem identification.

NLP and NLU techniques are becoming popular with chatbots. Chatbots can handle heart problem-related queries and answer them. Chatbots might use speech analysis and NLP methods for answering the questions. It is also important to identify the sentiments of the patients. During the conversation, positive and negative statements help in analyzing the sentiments using NLP techniques. NLP methods help in analyzing the why, who, what, when, where, and how of the conversation topics and queries of the patients. The patient might be in a context where the person is depressed, stressed out, in an emergency, sad, and agitated moods.

Different NLP methods are listed below:

- automatic text summarization
- sentiment analysis
- topic extraction
- named entity recognition
- aspect mining
- parts-of-speech tagging
- relationship extraction
- stemming

An automatic text summarizer helps in summarizing paragraphs of text into small sets or chunks. Extraction and abstract are the two methods of understanding a patient's problem. Extraction helps in the retrieval of the chunks from the paragraphs. Abstraction generates the summary from the retrieved chunks. Summarization techniques are listed below:

- LexRank
- TextRank
- Latent Semantic Analysis

LexRank is a summarizing technique based on the unsupervised graph. TextRank is also based on the unsupervised graph. LexRank has the feature to check similarity using the IDF-Modified Cosine method. LexRank finds summary in a patient's queries and summary does not have a similarity. Latent Semantic Analysis is based on data projection on low dimensional space. Word combination patterns in the corpus are spatially decomposed into singular vectors. Pattern importance relates to the singular value.

Sentiment analysis of the patient's queries helps in identifying three different moods or tones which are categorized as positive, negative, and neutral. This can be performed using supervised and unsupervised learning methods. Supervised learning model-based sentiment analysis is done by using naive Bayes. This method is based on a training corpus. The corpus has sentiment groups or categories. Heart Problems ML model can be created using the training data sets based on patient queries. The other methods are Random Forest and Gradient Boosting. Unsupervised learning methods used for sentiment analysis are lexicon-based techniques. The lexicon-based technique requires a corpus that has polarity and sentiment. Sentiment analysis helps in identifying the sentiment based on the polarities.

Topic extraction helps in finding the natural topics in the patient's queries in the conversation. It is based on an unsupervised learning method. In this method, training data and model training are not necessary. Topic modeling algorithms are listed below:

- Probabilistic Latent Semantic Analysis (PLSA)
- Latent Dirichlet Allocation (LDA)
- Correlated Topic Model (CTM)

Probabilistic Latent Semantic Analysis is a method for modeling using probabilistic heuristics. Topics are handled as latent or hidden variables in this method. This method can be done in two ways, which are the Latent Variable Model and Matrix Factorization. The latent Dirichlet Allocation method helps in identifying topics in a document. This method is based on the generative probabilistic method. This method is based on a Bag of words, exchangeable documents, and independent topics. The correlated Topic Model is based on the correlation of the latent topics for identifying topic relationships.

Named entity recognition (NER) helps in identifying the entities in the patient's queries. Concepts and references are identified in the patient's conversations. The entities which can be identified are:

- People
- Locations
- Organizations
- Dates

Aspect mining helps in finding multiple aspects of the patient's queries. You can blend this method with sentiment analysis to find information in the conversations. Part of speech tagging is one of the types of aspect mining.

Parts of speech are found in the patient's queries by parsing the text for nouns, pronouns, verbs, adverbs, prepositions, etc., The challenge in this method is related to a word can be in different parts of speech based on the context. Parts of speech tagging can be done using the following:

- Rule-Based POS Tagger
- Stochastic POS Tagger

Rule-Based POS Tagger is related to tagging parts of speech based on rules. Stochastic POS Tagger uses statistical methods like frequency-based and probability-based.

Relationship extraction is also based on rules, and it is the retrieval of semantic relationships from the paragraphs of text. These relationships are associated with more than two entities. Information extraction is about the retrieval of structured information using NLP. Information extraction is used in different areas mentioned below.

- Knowledge Graphs
- Question-Answering System
- Text Summarization

There are five different methods of doing Relation Extraction:

- Rule-based
- Weakly Supervised
- Supervised
- Distantly Supervised
- Unsupervised
- Rule-based

Rule-based relationship extraction is based on rules. Weakly supervised relationship extraction is also based on a set of rules, and new rules are added using iterative methods. Supervised relationship extraction is related to binary classifier training for identifying the relationship between two words. The classifier will have the following features:

- Context Words
- Parts of Speech Tags
- Dependency Path
- NER tags
- Tokens
- Proximity distance

Distantly Supervised relationship extraction is related to adding seed data to the classifier. Unsupervised relationship extraction helps in finding relations in the text based on rules, constraints, heuristics, and no training data.

Stemming is related to finding the root word from the word using suffix removal. Word inflectional forms are simplified to a common stem word. Inflection is related to words expressed in different forms mentioned below:

- Tense
- Case
- Voice
- Aspect
- Person
- Number
- Gender
- Mood
- Animacy
- Definiteness

The problem with this method where a single root can map to multiple stems. This problem results in overstepping and stemming which are referred to as false negatives. NLP and NLU methods rely on cardiology ontologies and cardiology knowledge bases related to the medical domains. These methods are based on Symbolic AI. Symbolic AI helps in creating a declarative model based on the cardiology knowledge of doctors and specialists. The declarative model has facts and rules. These models help in building an expert system for a domain based on deep medical knowledge bases. They help in text mining, machine translation, and automated question answering.

Chatbots are popular in conversing with patients and identifying heart problems accurately using the above techniques. Emergencies can be identified by sending help to the patient, which can save lives. The expertise in diagnosing cardiac arrest helps in saving a patient's life and assists in healthy living. The conversations can be in text or voice.

Voice analysis is used for text creation from the audio of the patient. Text created helps in identifying themes to calls, pattern identification, and query answering. NLP engine helps in finding threads and conversations. Sentiments are analyzed for tone, mood, emotions, utterances, and conversation topics. Historical conversations help in profile and behavior model creation. A sentiment is associated with the feeling of the user who is asking the query. That feeling can be analyzed using sound and voice.

Now let us look at how voice technology and speech processing can help in detecting and getting treatment for heart problems.

VOICE TECH - EMERGENCY SYSTEM

To start with, let us look at how voice processing works in a voice technology system.

Voice technology is becoming popular in the medical and health care vertical. Voice assistants are nowadays digital assistants for elder persons. Voice technology helps elder persons by alerting them about the Todos, meetings, and their schedule. Patients can use voice assistants through voice statements to share their medical record data and lab report data. Lab reports might be related to weight, blood pressure, and blood sugar. Patients can have nursing care through voice assistants for taking tablets and have a good diet schedule.

In the U.S.A, 112 million people use a voice assistant. Voice technology helps the patients with the following scenarios:

- to allow patients to call a nurse from the hospital (Robert-Shimonski, 2021) bed
- help doctors cut down on administrative tasks
- monitor their interaction with a patient
- improve efficiencies in the clinic
- facilitate clinical trials (Kerrie L. Holley and Siupo Becker M. D 2021)
- help chronically ill patients to manage their condition
- help the elderly with reminders and schedule
- in integrating the voice assistant into the EMR
- person's health condition
- to detect flare-ups in patients with chronic obstructive pulmonary disease.
- providing real-time information about the patient
- drafting notes from the doctor's conversations with the patient
- sharing reminders to take their medications and for doctor appointments.
- call the caregiver for emergency assistance
- to recollect their lives and improve their mood and share stories with family and friends;
- to encourage an active lifestyle.
- for coaching and help them with behavior-modification activities

Voice processing of the patient happens in the following stages:

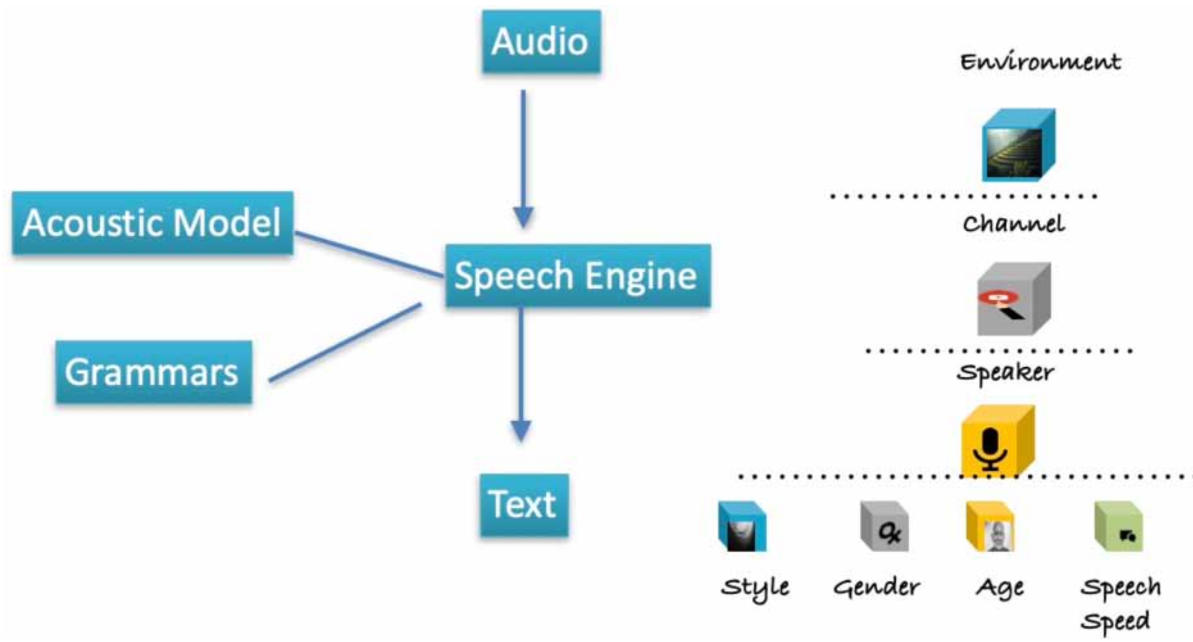
- Speech coding
- Synthesis
- Voice Recognition
- Speaker Recognition

Speech types can be categorized as:

- Isolated words
- connected words
- continuous speech
- spontaneous speech

Figure 2 shows the process of voice-to-text transformation.

Figure 2. Voice to text transformation



In figure 2, voice-to-text transformation is shown at component levels like audio, grammar, text, and acoustic models. The environmental conditions, speaker's style, gender, age, and accent are also shown as key factors to be considered in voice to text transformation.

Patients can be modeled as dependent and independent types. The Independent model focuses on the speech patterns of a large group. Dependent models are for a specific person. Patient speech diarisation is about dividing the audio stream into equal segments based on the speaker's identity. The patient's Speech transcription is based on the speaker's identity. Speaker can use vocabulary, which can be categorized as:

- Small
- Medium
- Large
- Very Large
- Out of Vocabulary

Voice systems are based on different factors such as

- environment variability
- channel variability
- speaker style
- sex
- age
- speed of speech

Voice processing and perception of the patient are about understanding the speech, translation of the language, and retrieval of features. Voice recognition and speaker recognition happen in the stages mentioned below:

- Analysis
- Feature Extraction
- Modeling
- Testing

Voice-based systems (Tom Lawry 2020) for detecting emergencies have dictionaries related to language and dialect. Dictionary words are used for identifying the speech words pronounced rightly. Dictionary will have parts of speech like the following:

- Nouns
- Pronouns
- Adjectives
- Verbs
- Prepositions
- Adverbs

Dictionaries will be updated frequently for cardiology-related changes and introductions. Medical Domain-specific terms and ontologies are also used for voice analysis.

The other method for a patient's speech recognition is template-based. Template-based helps in detecting the following:

- isolated words
- continuous speech
- Neural network-based recognition

Now let us look at the problems in identifying the patient and analyzing his or her speech. Pronunciation and grammar might impact the speech analysis. The precision of the speech analysis will depend on spontaneous voice vs reading-like speech. The audio recording and environmental factors impact speech processing. Speech analyses can be corrected manually for storage. The patient's speech can be validated for pronunciation and grammar. Speech analysis can create analytics (Robert-Shimonski, 2021) based on the following parameters:

- topics
- the emotional character of the audio
- locations of speech vs non-speech
- periods of silence.

Voice recognition of the patient process consists of recurring and voice-to-text transformation. Recording of the voice can be stored in a data source. The recording and transformation can happen in separate steps. Streaming of voice and analyzing the stream is another voice processing use case. The voice recorded can have voiced and unvoiced sounds. The recorded voice can be categorized as silence, unvoiced, and voiced sounds. Isolated utterances are detected using the stop consonants and endpoints.

In general patient's voice can have sentences, words, and phrases with or without grammar. The other important factors are language and dialect. The patient's condition might be another factor. Voice patterns can be related to the following:

- tone
- rhythm
- volume
- pitch
- cadence

A patient who has a cardiac arrest needs to get help from an emergency within 5 minutes. Every next minute patient's chances of living come down by 10%.

Voice technology-based emergency systems typically get calls from heart patients. 1000 patients get affected in a day in the U.S.A ad the survival rate is only 10%. It is observed to happen in healthy humans suddenly. Many use emergency help like 911 for getting treatments like CPR and AED. Critical conditions like OHCA can be identified quickly. Voice technology-based chatbots diagnose the patient's heart condition. Chatbots use AI and ML for analyzing the information to diagnose the problem using symptom knowledge. The patient's tone and his capability to breathe are checked during the problem diagnosis. The best AI/ML model helped in detecting the problem 40% better than humans. The chatbot could identify the symptoms 25% faster than the human representative.

The models can be improved by adding the questions, and conclusions, and improving the cardiology and medical knowledge base. The chatbots and digital assistants can help in scenarios that involve ambulances, emergency rooms, and general health care centers. In the COVID-19 pandemic period, chatbots are becoming popular because of the capability of updatable medical knowledge bases.

DEEP LEARNING

Deep learning is deep structured learning. It belongs to the category of machine learning AI based techniques. The deep learning model has multi-processing layers. The layers process the data which is the input and pass it through different layers which identify the specific patterns and representations. These layers classify the data based on the type of input. Deep learning has been applied in various fields such as drug discovery, development, bioinformatics, plant genomics, toxicology, and genome analysis. Computer vision and machine learning are also used for remote health monitoring and health care data analysis.

Deep learning-based AI techniques are popular these days to detect heart problems. CNN-based methods are being used for audio, video, and image processing in the medical domain. Medical images like X-rays and lab reports are analyzed for diagnosis using CNN (convolutional neural network).

The convolutional neural network method has two stages which are convolution and pooling. The basic characteristics of the lab reports are reduced during the stages. Convolution is about dividing the heart problem-related lab reports into smaller pieces. The convolutional neural network typically has more than one convolution and activation layer. The convolution layer is a filter that works on the dot product of the content's input values and assigned weights. For example, the output sum can be for filtering the X-ray report pixels. The activation layer helps in reducing the heart problem-related content to a small matrix. The backpropagation algorithm is used for network training in the activation layer. ReLu function is executed in the activation layer. The pooling stage reduces the filter size and sampling down the lab report data. The network is trained using the different features of the lab report content, which is unstructured. A multi-layer perceptron is a fully connected layer in CNN. The input vector for this layer is single-dimensional. The output result is also a single-dimensional vector. The result is based on a group of feature label probabilities. Labels stand for the class and classification decision is based on the higher probability.

Neural network methods like ANN, CNN, LSTM, and RNN are popular. AI open source and commercial software packages are listed below:

- Google Tensor Flow
- IBM Watson
- Scipy
- Azure ML
- Keras
- Google AI
- NTLK
- Pytorch
- AWS Sage Maker

Now let us look at ANN (Artificial Neural network). ANN is based on a human neural network. An artificial neural network consists of more than one node. Nodes are connected using links. Nodes can interact with one another. Input data is sent into the nodes and they can perform operations on the data. The output node is referred to as activation, and the node value is represented by the weighted sum of the node values. Artificial neural networks are categorized as FeedForward and Feedback types. FeedForward Artificial neural network is based on a unidirectional flow of information through the network. There are no feedback loops in the FeedForward ANN. IT has fixed input and results. FeedBack Artificial Neural network has feedback loops, and it handles content-addressable memories.

A recurrent Neural Network (RNN) is based on a standard neural network with the input of series type. RNN helps in keeping the history and making decisions based on the history. A Recurrent Neural network can have a hidden state vector related to the context. RNN reads the inputs in a sequential way and transitions are applied in a non-sequential way. A recurrent neural network can work on hierarchical tree graphs which consist of parent and child nodes. A deep recurrent neural network can find the relationship between the input and depth of RNN will be related to hidden layers, hidden to hidden transitions, and hidden to result in transitions. A bidirectional Recurrent neural network helps in correcting the past based on the future. This is used in speech and handwriting scenarios. Encoder decoder/ Sequence to Sequence Recurrent Neural networks are helpful in language translation. Two Recurrent neural networks are used as encoder and decoder. The encoder updates the hidden state and creates the context result. The decoder reads the result to translate the context to the result set. Long short-term memory networks (LSTM) are based on vanilla Recurrent neural networks and have gates and cell states to reset the context. Gates are used for addressing the issues with long-term dependencies. The above techniques are used for EEG and ECG analysis. Deep learning methods are applied for the analysis of patients' information to detect and predict cardiac arrest problems. ECG is used for analysis to predict (Tanzila Saba, Amjad Rehman, et al. 2022) cardiac arrest before 24 hours of occurrence. ECGs classified as cardiac arrest-based is used in the classification and training process. Wearable devices are used for identifying and analyzing heart problems.

Now let us look at the wearables, which can help in preventing and detecting sudden cardiac arrest.

WEARABLES

A defibrillator wearable helps the patients to detect and prevent sudden cardiac arrest. Defibrillator based wearables can be as below:

- Transvenous Implantable cardiac defibrillator (ICD)
- subcutaneous ICD (S-ICD)
- wearable cardioverter defibrillator (WCD)
- left ventricular assist device (LVAD)

An implantable defibrillator helps patients using the ventricular tachycardia (VT)/ventricular fibrillation (VF) technique. This also helps patients who have haemo-dynamically significant ventricular tachycardia. The implantable cardiac defibrillator is for patients who had a heart attack and they can wear it after 40 days from the day of heart stroke and 90 days after bypass surgery.

The implantable cardiac defibrillator technique helps in preventing the following heart conditions:

- ischemic and non-ischemic cardiomyopathies
- congenital heart disease conditions
- inherited channelopathies
- cardiac resynchronization therapy (CRT-P)

Research studies have shown usage of an Implantable cardiac defibrillator helps reduce the risk of death. Some patients get an automatic emergency cardioversion defibrillator (AED) instead of an Implantable cardiac defibrillator. An implantable cardiac defibrillator is used by the following patients

- after revascularization
- myocardial infarction problem
- cardiomyopathy
- active infection
- unknown prognosis

During the treatment and diagnosis using the wearable, Left Ventricular Ejection Fraction (LVEF) helps in tracking the health of the patient. Normal LVEF condition refers to 65% of the left ventricle blood being pushed with every heartbeat. Typically, ejection fraction changes based on the heart problems and the treatment. It is observed the ICD helps in a 10% positive change in Left ventricular ejection fraction for cardiomyopathic patients.

There are limitations to the ICDs which are listed below:

- ICDs can have a component failure
- They can lead to a dysfunctional state
- They can create inappropriate shocks
- vascular oclusión can happen in patients
- infection might be caused
- skin erosion can happen

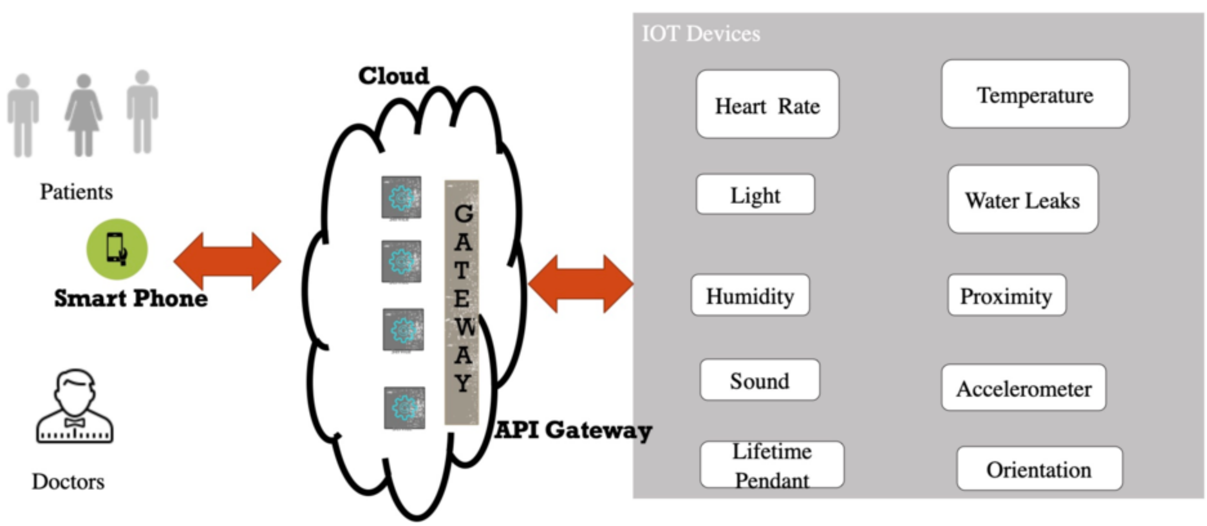
A wearable cardioverter defibrillator (WCD) can help in identifying ventricular tachyarrhythmias and preventing sudden cardiac arrests. The other treatment can be mechanical circulatory support.

Patients can also receive the following treatments:

- cardiac resynchronization therapy (CRT-P)
- cardiac magnetic resonance imaging (cMRI)

The presence of late gadolinium enhancement (LGE) helps in detecting sudden cardiac arrest. There are other wearables like smartwatches and wearable heart rate monitors which help in finding heart problems. Athletes can use these to identify arrhythmias early before it becomes life-threatening. A software platform that integrates with the wearables can help in remote cardiac monitoring of athletes by doctors. Sudden cardiac arrest is the cause for around 350 k people in the athlete's group. Wearables help in avoiding the non-screening of heart problems. 80% of the heart issues are due to non-screening. NIH research data shows 62 cardiac problems in the athlete's data, which consisted of 2640 patients' heart data. 50% of the cardiac deaths (24 out of 62 were deaths) were unexpected and first-time for the patient. Young athletes can be a target for sudden cardiac arrests due to high-stress conditions in the U.S.A. Figure 3 below shows the IoT Cloud interaction with wearables and sensors.

Figure 3. IoT cloud - wearable & sensors



In the above figure, the IoT cloud is presented which gathers data through an API gateway. Devices and sensors send data related to heart rate, light, humidity, sound, vital signs, temperature, water conditions, speed, and movements to the API gateway which is stored on the IoT cloud. IoT apps consume the data to present dashboard-like features to the patients and doctors.

Wearables help in identifying the abnormal heartbeat in the patient. False positives might come off the data due to less precision. Wearables alert the patients to check with the doctor for a check-up. They can help in detecting arrhythmia and it can be enhanced to gather more information about the patient. Remote Cardiac monitoring devices certified by FDA can help the patients and doctors in high-stress scenarios. These devices share the heartbeat to the cloud and physicians can access the information using mobile and desktop applications.

Now let us look at the smart devices and how they can help out in the heart monitoring of the patients.

IOT - SMART DEVICES

IoT – Introduction

Internet of things (IoT) is a very popular term for a sensor/device-based network communicating for a goal. Internet of things in health care is used for hospital asset tracking. Hospital assets can be patient's carts, oxygen pump equipment, defibrillators, sleeping beds, operating equipment, and other medical equipment. IoT devices are used for monitoring medicines, vaccines, and patients for ideal environmental conditions. They are also used for monitoring patients' vital signs, sleep, and remote care. They can be used for receiving alerts related to medical refills and sending emergency signals to the hospital and emergency transport. IoT can help in improving patient care and doctors' decision-making. Transportation time, disease identification, and health drug delivery can come down due to the usage of IoT sensors.

Real-life examples where IoT is used in hospitals are:

- Remote monitoring and care for patients
- Monitoring of Glucose and Blood pressure
- Monitoring of Heart Rate
- Patient's Hygiene monitoring
- Monitoring the psychological condition of the patient
- Monitoring of memory-related brain condition
- Inhaler – sensor-based
- Sensors that are ingestible into a human body
- Eye contact lenses – sensor-based
- Sensors and devices for robot-based surgery

Sensor Data Integration

Data fusion is an evolving area that is related to sensor data integration and the creation of knowledge bases. Data Fusion helps in providing contextual information, user involvement, etc., from the knowledge bases and databases. Deep learning, Data fusion, and Data mining of the healthcare data help in identifying potential issues. These technologies can determine the cause-effect relationships with the environment. Data collated from sensors, mobile devices, fitness devices, (Harry Glorikian and Dr. Bob Arnot 2021) and smart city infrastructure helps in identifying critical issues which require immediate action.

Heart rate patterns can be detected by using smart devices and sensors. smartphones, wearables, and implantable devices can help in tracking the patient's heart condition. The sensors can be used for measuring:

- ECG
- EEG
- Temperature

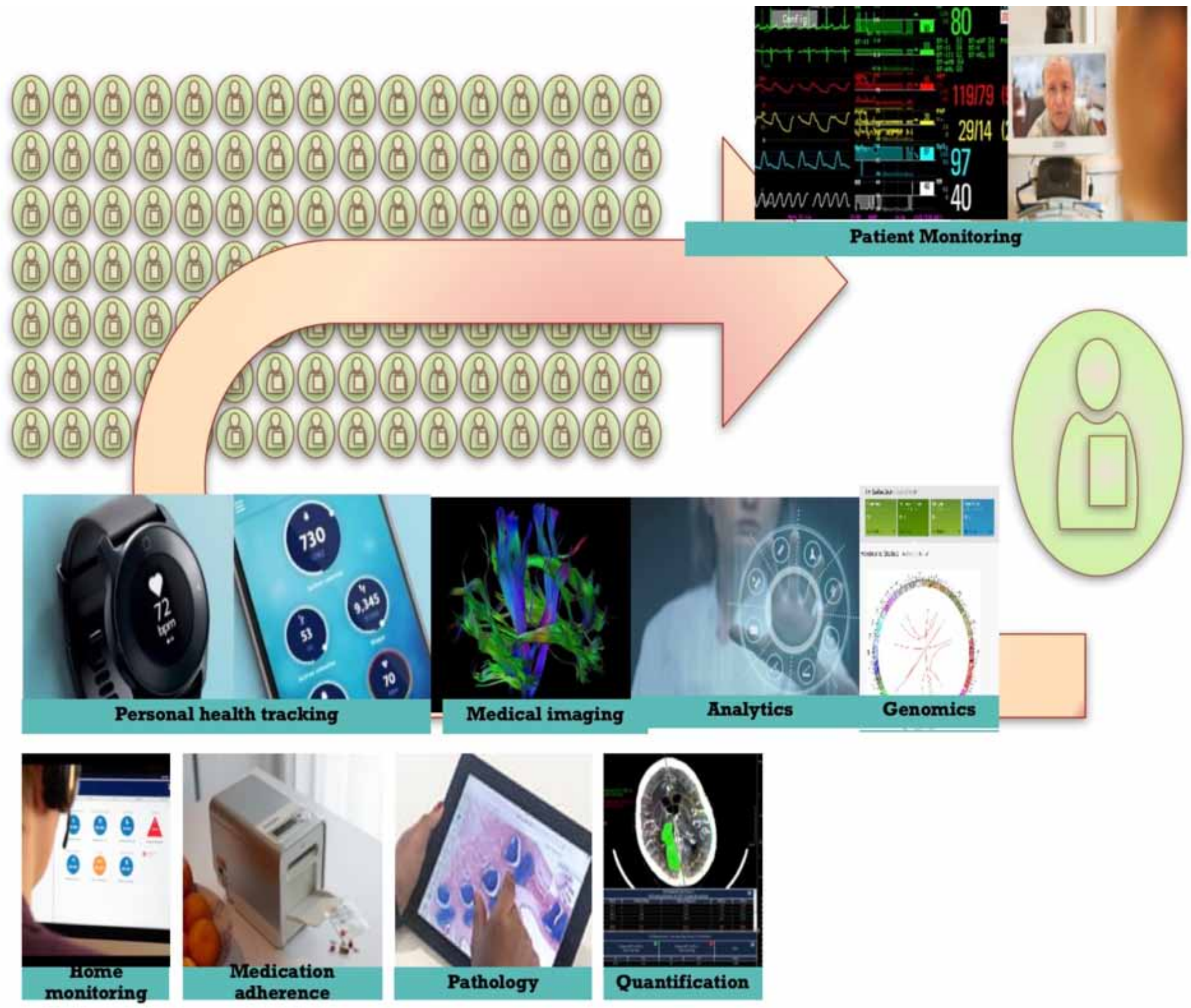
The sensors data can be used for detecting and predicting heart problems based on the trained AI/ML model (Bernard Nordlinger, Cédric Villani, et al. 2021). The analysis of the sensors data comes up with the following results:

- heart rate
- RR intervals
- ST-segment

Note: RR interval is the duration between two sequential R peaks in an ECG signal. ST segment is the flat portion of the ECG signal. The flat portion lies between the end of the S wave and the beginning of the T wave.

A heart monitoring system integrated with sensors uses the AI/ML (Arjun Panesar 2019) model to identify the abnormalities. Smart devices can also measure breathing patterns which help in detecting the gasp which happens in a sudden cardiac arrest. Smartphones or desktop speakers can be used to alert emergency care centers. Detection of gasps of breath during sleep is another scenario where smart devices can help. Research study shows that 0.5 million people in the U.S.A die due to sudden cardiac arrest and it happens in sleep. This observation is threatening for heart patients, as during sleep there is nobody to help. Smart devices help in this scenario to prevent life-threatening situations.
Figure 4 below shows the heart monitoring system details.

Figure 4. Heart monitoring system



In figure 4, the heart monitoring system is shown which has home monitoring, pathology, quantification, medication adherence modules, or equipment. Patient monitoring, personal health tracking, analytics presentation, medical imaging, and genomics-related data gathering are some use cases for this system.

“This kind of breathing happens when a patient experiences really low oxygen levels It’s sort of a guttural gasping noise, and its uniqueness makes it a good audio biomarker to use to identify if someone is experiencing a cardiac arrest.” , ” - Dr. Jacob Sunshine, a researcher

The heart monitoring system can use breath sound recordings for training. Emergency calls can be used for analyzing in real-time if the patient has a heart problem. The noise factors due to the following are added to the training data.

- sounds of cats
- cars honking
- dogs barking

- air conditioning
- home interior sounds

This system uses smart speakers at home to constantly monitor the patient's conditions like breathing, heart rates, and pulse rates. The prediction will be done in real-time for sending emergency help to the patients who are in life-threatening situations.

Sudden cardiac arrests are the cause of death in North America. Out of hospital deaths (OHCA) are higher and 300k patients die every year. It is observed that the death is due to the following reasons:

- disordered breathing
- agonal breathing
- gasping breaths

Note: Agonal breathing happens due to brainstem reflex in the setting of severe hypoxia

The integration of smart devices like smartphones, speakers, and audible biomarkers into the heart monitoring systems helps in the prevention and detection of sudden cardiac arrest conditions in heart patients. Emergency health care centers need to have heart monitoring systems integrated with call centers and help can be provided by dispatching CPR treatment devices to the patients.

The challenges in creating this real-time monitoring system are:

- patient sensors integration from home location to the cloud
- agonal breathing scenarios are sudden
- reproduction of agonal breathing is tough
- snoring and obstructive apnea events can create confusion
- accuracy of capturing sounds due to environmental factors.
- patient's privacy is another issue
- patients prefer contactless devices as sensors
- historical data of agonal breathing sounds do not have the right amount of data

TECHNICAL ISSUES

AI, Wearables, Chatbot, and IOT has great advantages in implementation. On the other hand, there are many issues and challenges with these technologies. The errors caused due to these technologies can cause side effects/ injuries, and give wrong predictions to the patients. The implicit confidence in technology vs explicit human error is perceived differently by the patient and the doctor. AI systems rely on big data for accurate results. Cold start scenarios in the hospitals can give wrong predictions if not properly populated with big data. Big data required can be dependent on the geography and demographics of the patient in context. The other challenge is that data required can be from different systems and it is most of the time collated as a separate part of the whole data. This can cause errors and the risk also increases for the patient.

Privacy of the patient is a big challenge as most patients are not interested in sharing their medical data. Improving upon the existing solution by having a feedback loop might not work if the patients are worried about privacy issues. This might lead to data bias as most of the scenarios are not captured well in the testing and training data. The other area where medical professionals are worried about automation might cause a decrease in the skills of human medical professionals. This might lead to scenarios where errors might not be caught by the doctors and skilled professionals in the hospital. Reaching a high level of perfection is a big problem as humans will never look out for improved options in medical research.

Many initiatives are happening in different countries to digitize data and create electronic health records in a citizen medical database. As discussed above, many hurdles are faced by health professionals in digitalization of the health records. The exchange of health records for research is impacted by privacy and legal issues posed by the patients. The lack of data in AI systems might cause predictions that can be understood by doctors. The human body is mysterious, though it is similar it does not function the same as others, with AI systems the computer analyses pre-fed data with a certain algorithm, therefore, AI needs to update with the latest trend to meet requirements. The AI-powered solutions don't think out of the box if there are any deviations from the fed data the AI fails to recognize the complication or ends up giving varied results.

WHAT'S NEXT

AI/ML, IoT, Sensors, Wearables, and Smart devices technologies are evolving and helping patients to detect the heart condition very early before it becomes life-threatening. The goal is to build a sudden cardiac arrest monitoring system that is contactless.

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KEY TERMS AND DEFINITIONS

1D: One-dimensional.
2D: Two -dimensional.
ACE: Angiotensin-converting enzyme.
AED: Automatic emergency cardioversion defibrillator.
ANN: Artificial neural network.
AUROC: Area under the receiver operating characteristics curve.
CI: Confidence interval.
CNN: Convolutional neural network.
CPR: Cardiopulmonary resuscitation.
CRT-P: Cardiac re-synchronization therapy.
CTM: Correlated topic model.
DLA: Deep-learning-based artificial intelligence algorithm.
ECG: Electrocardiography.
EEG: Electroencephalogram.
Grad-CAM: Gradient-weighted class activation map.
ICD: Transvenous Implantable cardiac defibrillator.
IRB: Institutional review board.
LDA: Latent Dirichlet allocation.
LSTM: Long short-term memory networks.
LVAD: Left ventricular assist device.
NLP: Natural language processing.
NLU: Natural language understanding.
OHCA: Out of hospital cardiac arrest.
PLSA: Probabilistic latent semantic analysis.
RNN: Recurrent neural network.
RRS: Rapid response system.
S-ICD: Subcutaneous ICD.
SCA: Sudden cardiac arrest.
SCD: Sudden cardiac death.
STEMI: ST-segment elevated myocardial infarction.
SVM: Support vector machine.
TTS: Track and trigger system.
WCD: Wearable cardioverter defibrillator.

Chapter 4
Sudden Cardiac Arrest Detection by Feature Learning and Classification Using Deep Learning Architecture

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ABSTRACT

Ventricular tachycardia (VT) and ventricular fibrillation (VF) are known ventricular cardiac arrhythmias (VCA) that promote fast defibrillation treatment for the survival of patients and are defined as shock-oriented signals, perhaps the most common source of sudden cardiac arrest (SCA). The majority of existing VCA classifiers confront a difficult challenge of accuracy rate, which has generated the issue of continuous detection and classification approaches. In light of this, the authors present a feature learning strategy that uses the improved variational mode decomposition technique to detect VCA on ECG signals. The following SCA consists of a deep convolutional neural network (deep CNN) as a feature extractor and bat-rider optimization algorithm (BROA) as an optimized classifier. The MIT-BIH arrhythmia database is used to examine the approaches, and the analysis depends on performance indicators such as accuracy, specificity, sensitivity, recall, and F1-score.

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INTRODUCTION

Sudden cardiac death (SCD) is an important mortality factor that can be avoided. It is predicted to have a global annual prevalence of 5.2 million individuals (Rajendra Acharya et al., 2020). SCD is described as a heart failure that happens around 24 hours of the onset of symptoms perhaps within 24 hours after the last time the sufferer had been seen well (Sielski et al., 2021). The heart stops pumping or ceases to beat properly in heart failure, resulting in termination of the oxygen supply on the entire body leading to a shortage in flowage of blood. Ischemic brain damage occurs within seconds of cardiac arrest (Gentile et al., 2021) (Raziani et al., 2021), providing only a narrow time frame for treatment to prevent SCD. Ischemic heart disease causes the majority of SCD patients, however primary arrhythmic disorders are frequent in persons under the age of 30 (Nguyen et al., 2018). Early electrocardiographic (ECG) detection of abnormal electrical vs. normal electrical rhythm during circulatory collapse is critical, irrespective of the aetiology (Crea et al., 2021). By recovering the appropriate heart pumping rate, the shockable ECG signals such as VF and VT can return to standard sinus beat. Shock therapy, on the other hand, will not restore sinus rhythm or cardiovascular flow in non-shockable beats such as asystole or pulse-less electrical impulses (Tripathy et al., 2018), wherein electromechanical divergence prevents cardiac shrinkage despite an organized electrical heart rate. Artificial intelligence (AI) techniques have indeed been frequently integrated into the Computer-Aided Arrhythmia Classification (CAAC) scheme that improves overall accurateness by smart identification of shockable ECG rhythms, providing certain prognosis management that is premised on the appropriate ECG analysis throughout the cardiac arrest. The bulk of SCDs happens outside of the hospital, where ECG detection and treatment are unavailable, resulting in poor survival and cerebral outcomes disorders (Hagiwara et al., 2018). AED devices are commonly employed in the event of cardiac arrest to distribute electrical pulses to the heart to restore a stable heartbeat (Kranc et al., 2021). The establishment of innovative CAAC systems and associated AI-based methodologies is motivated by expanding development of accurate ECG rhythm diagnosis.

Figure 1. The architecture of ventricular arrhythmia detection

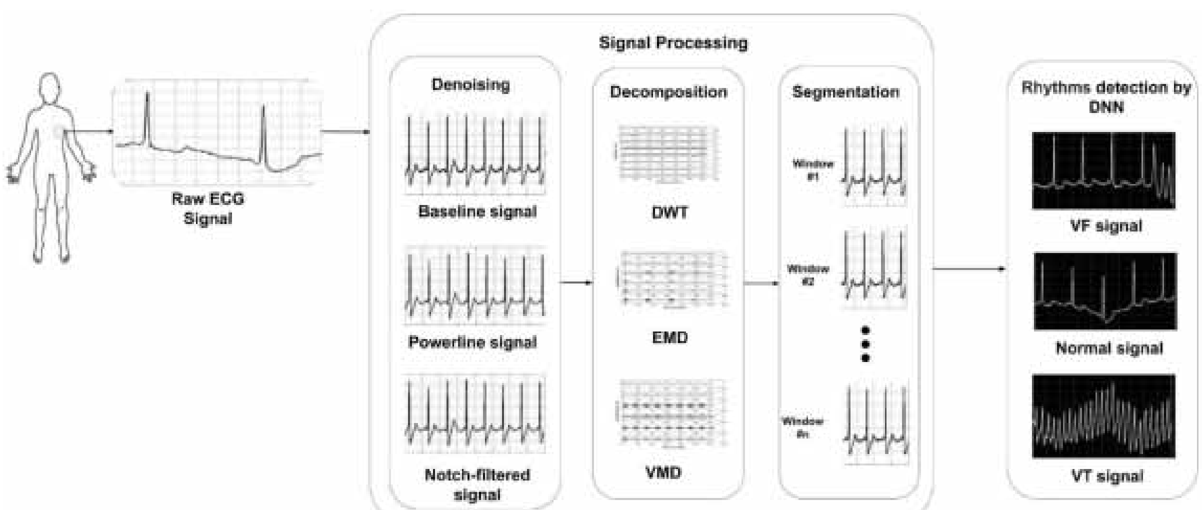


Figure 1 (Sabut et al., 2021) shows the usual approach for detecting ventricular arrhythmias, which includes ECG data gathering, dissection, feature extraction, and categorization. A high-pass filtration is done to reduce baseline drift, while a notch filter was used to eliminate powerline disturbance. The VF, VT, and normal occurrences were picked from ECG signals using a 5-second interval and then de-noised using the wavelet and decomposition methods. To create a big hybrid dataset with more dimensions, there is a requirement of time-domain ad frequency domain-oriented characteristics, which can be used to improve the composite methods.

Deep Learning (DL) is a phrase that relates to research by extraction, forecasting, and intelligent decision making, or, to put it another way, recognizing layers using a set of information, referred to as training data (Joshi et al., 2022). DNNs are more scalable than traditional learning methods because improved accuracy is typically attained by raising the capacity of the network. Several Deep Learning (DL) models, such as the dimensional Convolution Neural Network (Dinakarrao et al., 2019), AlexNet version architecture, and Deep Belief Network (DBN), have indeed been presented in the latest days to enhance the precision of various learning tasks. The improvement in the neural network can be done by reducing the time consumption while constructing the layers so that the delay can be reduced in the overall network (Gharehbaghi et al., 2019). Even though the concept of a deep-time developing neural network is well-suited for biosignals, particularly some with periodic properties, its applicability to Attribute selection is still to be investigated.

DL approaches have limits, despite their success in boosting classification performance when compared to older machine learning methods. Deep networks are computationally costly for processing construction with a large memory footprint. As a result, DNN-based arrhythmia classification software is predominantly used on CPUs and/or GPUs and it is not a realistic solution (Piccirillo et al., 2022). As a result, present DNN hardware implementations are too large to be used on power-constrained wearable components. The suggested deep learning approaches are effective for a restricted number of arrhythmia categories, as per the research articles. Owing to the difficulty of building the classifier and the materials needed, creating a complicated model for categorizing all ECG arrhythmia has not been demonstrated to be useful. The majority of the publications examined concentrated on ECG amplitude and phase; nevertheless, various essential factors such as the patients' physical status (e.g., time of life, gender, medical problems, behavior, and so on.) remain unaccounted for in the field (Sayantan et al., 2018).

Convolution neural classification has been demonstrated to be successful for arrhythmia classification, as per the best classification techniques provided. Dynamic classification algorithms are smart enough to process two types of components such as long and short term efficiently in all scenarios (Yildirim et al., 2018). The basic architecture of CNN can be able to perform well for classifying the different types of arrhythmia powerfully and hence it can be considered a significant architecture for this work.

The rest of this chapter is ordered as follows - Section 2 mentions a few existing research works, Section 3 shows the proposed approach and methodologies, Section 4 exhibits the experimental outcomes and discussion, and, finally, Section 5 ends up with a conclusion and future work.

RELATED WORKS

Several research has demonstrated the potential of neural networks to classify cardiac arrhythmias. Nevertheless, these studies are mostly focused on and evaluated single-lead ECGs, whereas multiple-lead ECGs record heart activity in several ways.

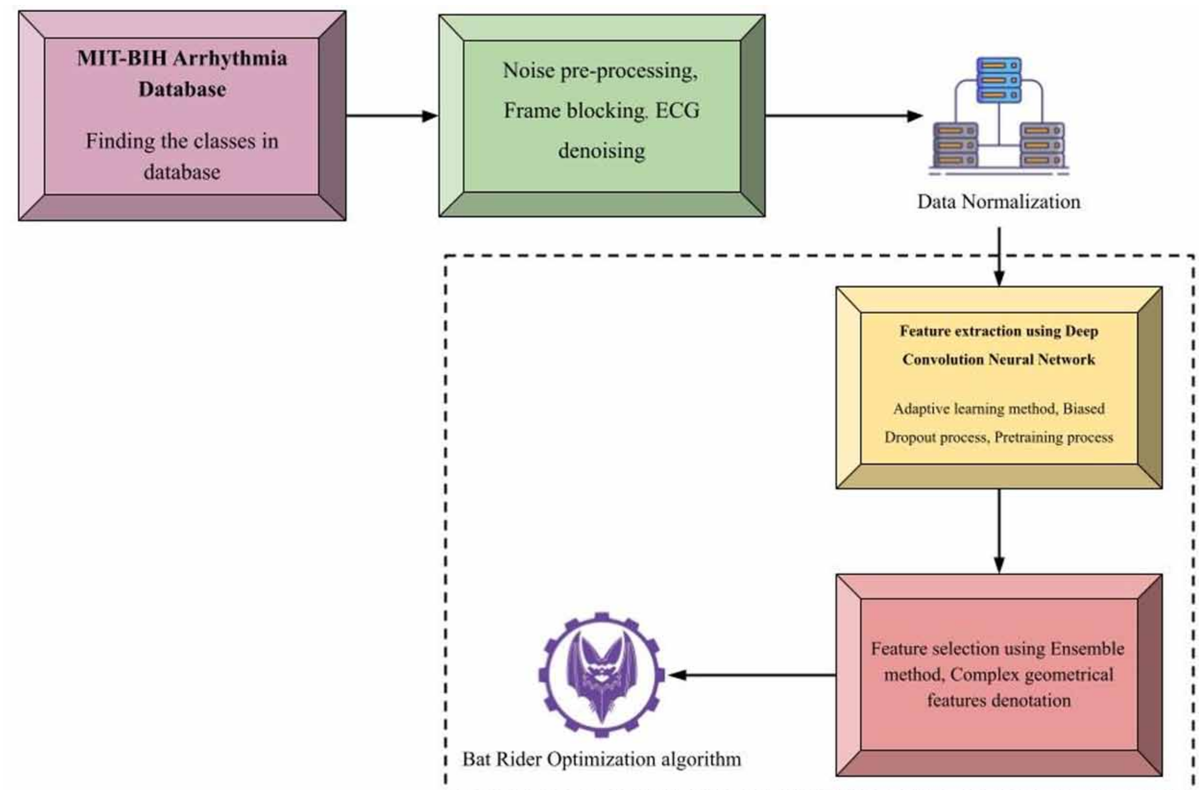
Deep convolutional neural network (CNN)-based techniques for authentic arrhythmia detection were used (Wu et al., 2020). Firstly, they created a deep convolutional network model with higher levels. This model achieved standard state-of-the-art performance on the PhysioNet/CinC AF Classification Competition 2017 dataset with the assistance of preprocessing. Systems with poor computer resource needs are preferable. A binarized model utilizes substantially less computational speed and storage space than a full-precision model, according to research. Using a Cascaded Convolutional Neural Network (CCNN) and subjective description manner, (Yang et al., 2021) offers a 12-lead ECG arrhythmia classifier model. First and foremost, the one-dimensional (1-D) CNN is intended to automatically remove the features from the individual lead indicator.Following that, features are concatenated as a contribution to two-dimensional (2-D) densely linked ResNet modules for categorizing the arrhythmia, taking into account temporal relationships and spatial scales among different leads. In (Allam et al., 2020) the author suggested a method for improving ECG beat arrangement by fixing the little quantity of training data using Stockwell transform (ST) and two-dimensional residual network (2D-ResNet). ST delivers time-dependent and amplitude-dependent dynamic resolution when converting an ECG signal to a time-frequency region. As suggested by the National Association of Biomedical Technology, the resulting ST pictures are used as information for the suggested 2D-ResNet to categorize various modes of ECG signals among patients. The Optimum Recurrence Plot based Classifier (OptRPC) is a nonlinear process approach for categorizing the ECG rhythms by integrating them in the higher - dimensional way by developing an optimized recurrence plot, as described in (Labib et al., 2022). These recurrence graphs are then classified using a Convolutional Neural Network design. An innovative and computerized technique for Local Feature Subset Selection is utilized by (Ebrahimzadeh et al., 2019) by picking the rigorous methodologies for features extracted in a nonlinear manner, where the time-frequency and classic properties are developed in earlier publications. As a result of the activity of best feature assortment by fixing proper interval between every signal propagation, that can able to choose features that diverge from each other in each minute before the incident. Utilizing a 2-second subdivision of 2D recurrence plotted images of Ecg data, the author constructs a new deep learning algorithm for successfully diagnosing arrhythmia (Mathunjwa et al., 2021). The ventricular fibrillation (VF) classes can be differentiated throughout the first stage. The atrial fibrillation (AF), normal, early AF, and early VF categories were separated in the second phase. The author (Huang et al., 2019) suggested a two-dimensional (2D) deep convolutional neural network technique for ECG feature classification. Moreover, Fourier transform was opted to exchange the ECG wavelet packet impulses into frequency domain spectrum analyzer for detecting dissimilar heartbeat such as, Premature ventricular contraction pulse left bundle branch block pulse, right bundle branch block pulse, and atrial premature contractions pulse. Following that, the ECG arrhythmia categories were recognized and categorized using the spectrograms of the five arrhythmias. Because of its exceptional quantitative feature extraction capacity, the gray-level co-occurrence matrix is used for feature vector characterization as indicated in (Sun et al., 2019). Furthermore, the resulting 3D multi-scale GLCM is dynamically categorized using the convolutional neural network (CNN) technique. Investigations showed that the suggested method is quite effective at detecting morphological arrhythmias. Such findings indicate that the GLCM descriptions can accurately recover the geometry characteristics vector from lead ECGs with strong clinical outcomes for a wide range of different arrhythmias. The author (He et al., 2019) suggested a new deep neural network architecture for automatically classifying arrhythmias (DNNs). The 2 DNN classifiers are skilled to retrieve the characteristics from the original ECG signals using the residual layer, dropout layer, and aggressive layers. These retrieved features are combined into a feature vector, which will then be trained to perform the final classification. Represent a new Multi-Lead-Branch Fusion Network (MLBF-Net) topology for arrhythmia categorization that integrates multi-loss optimization to simultaneously acquire multi-lead ECG heterogeneity and consistency (Zhang et al., 2021). The constructed architecture is made up of 3 parts: 1) manifold push branches to process the uniqueness of multi-lead ECG; 2) bridge the extracted features by fashioning the authenticity of multi-lead ECG by appending the output local features of all branches; 3) construction of multi-loss layer for all local branches and the cascaded system. Using the VF filter leakage characteristics, spectral characteristics, are detected as shown in (Alwan et al., 2018), which produced a detection performance of 73.5% using a machine learning classifier when identifying VT and VF. The high-dimensional set of features maintains more essential information within ECG data, resulting in a 73.5% accuracy rate. Such approaches, on the other hand, are largely considered as time domain-oriented characteristics produced by any of these methods and classified using common classifiers such as artificial neural networks and SVM classifiers. These techniques showed promise in forecasting VT and VF; nevertheless, because VA is a critical heart arrhythmia, its forecast rate needs to be improved at a quicker speed.

The aforementioned studies demonstrate that a deep neural network can understand complicated representative attributes in an unsupervised manner dynamically, reducing the manual features selection and allowing to generate of end-to-end learning methods that take ECG signals as input and forecast arrhythmia class as outcome while retrieving the "deep features" (Salem et al., 2018). DNNs, on the other hand, demand a large quantity of data in the testing phase as compared to conventional classification algorithms. Because the datasets that are publically available in this sector are small, this issue generates a gap between computational complexity and feature level.

SYSTEM MODEL

Initially, the MIT-BIH Arrhythmia Database is executed for finding the classes. The pre-processing of the signal takes place to reduce the noise and frame blocking followed by data normalization. Next Feature extraction is carried out using Deep Convolution Neural Network by adopting an Adaptive learning method, biased Dropout process, and pretraining process. After extracting the features, the required features are selected using the ensemble method. Finally, the Bat Rider Optimization algorithm helps for proper classification of the presence of cardiac arrest or not.

Figure 2. Block diagram for classifying the presence of cardiac arrest



DATASET DESCRIPTION

The ECGs in the MIT-BIH Arrhythmia Database come from a collection of over 6000 lengthy Holter recordings taken between 1975 and 1979 by the Beth Israel Hospital Arrhythmia Lab. Hospital patients provided around 60% of the data. This database includes 23 records (numbered 100 to 124 inclusive, with some statistics losing) random selection from this series, as well as 25 records (numbered 200 to 234 accessible, including some statistics losing) chosen randomly from the same set to portray a diverse range, but signiðcant manifestations which cannot be given as a comparatively tiny indiscriminate illustration of Holter recordings. Several of the 37 tracks are somewhat more than 27 minutes. Segments have only been discarded if none of the two ECG signals have been of good enough quality to be analyzed by human experts. Nonlinear ventricular, junctional, and supraventricular arrhythmias, as well as transmission anomalies, were included in the second batch of records. A few of these recordings are selected since the signal, QRS morphological fluctuation is visible. Hence, these records have attracted a lot of attention from database users. The participants were 25 men and 22 women, between the age of 32 and 89-lifetime duration.

CLASSES IN DATABASE

ECG signals from 5 categories are included in this dataset: 'N'- 0, 'S'- 1, 'V'- 2, 'F'- 3, and 'Q'- 4. These categories' ECG signals have the qualities listed below. With a maximum of 1,09,446 samples comprising the 5 aforesaid classes, the Eeg data given in the database are rendered at a sample occurrence of 157 Hz.

Normal, Left or Right packet root, Atrial escape, and Nodal escape are all in the 'N' category.

Atrial Premature, Aberrant Atrial Premature, Nodal Premature, and Supra-ventricular Premature are all classified as 'S' signals. 'V' Category is showing Premature ventricular contraction and Ventricular escape

Integration of ventricular and normal is labeled as 'F', while paced, synthesis of paced, and standard Unclassifiable are labeled as 'Q.'

Noise Pre-Processing

Interferences from inputs such as power-line disturbance, muscular contractions, and baseline drift generally pollute them, blurring the properties of the ECG signals for categorization. Original ECG signals in the databases are hence noise reduced denoised with the help of a five-order Butterworth lowpass (45 Hz) filter to eliminate interference and remove background fluctuation, with the goal of limiting the belongings of pollution on the representation unit.

Frame Blocking

In this investigation, a frame blockage strategy developed from cardiac electrodes is used to unify the duration of several ECG recordings. Frame blockage, hence split signals into short, overlapping frames, allowing for a smoother transition between neighboring frames while maintaining data integrity. Due to the closeness among signals and ECG time sequence, the frame blockage approach is capable to standardise the recording duration of ECG signal. Each frame is differentiated with its unique length, for instance L_l is the length of the l-th frame which is given by

$$L_l = L_s + l \tag{1}$$

The raw ECG signal may have a total length of G_l, with the total number of frames can be given by L_n with the length L_l, Hence, the equation can be expressed as

$$L_s = (G - L_l) / (L_n - 1) \tag{2}$$

We adjusted L_l and L_n to 500 (sampling points) and 15, correspondingly, to keep as much of the accessible ECG signals at every record as feasible, but we used the L_s variable to match the duration and count of frames.

ECG Denoising

An ECG signal is a less-amplitude signal with a frequency band between 0.3–40 Hertz and a signal amplitude must be lesser than 200 mV. The factors namely, noise, myoelectric interference, baseline float, and spectral interference, can contaminate such faint signals, hence recorded ECG observations frequently. The cutoff was determined using the Stein impartial likelihood approach and the Daubechies wavelet basis operator. A depiction of an ECG signal before and after denoising is done. Note that the ECG signal's amplitude was normalized to the interval [0,1].

Data Normalization

Data normalization's major goal is to increase performance by reducing the impact of features with massive data quantities on the classiðer. For data normalization, the suggested method uses a centering and resizing method for the dataset which further increases arithmetic consistency. The centering adjustment is done to bring the average value of features down to zero. After centering a set of data e such that e= $\{e_1,e_2,e_3,\ldots,e_n\}$ awe get a new set of converted observations given as

$$Cen_{xi} = \{x_i - \mu(\mathrm{x})\} \tag{3}$$

where, $cen_x = cen_{x1}, cen_{x2}, \ldots, cen_{xn}$ and n is the sum of observations, and the resulting mean $\mu(cenx_)$ equals 0

After centering, a scaling transition is used to give cen_x a one-standard-deviation standard deviation. The scale conversion is based on the division of every data in cen_x by the standard deviation of all data in set x and is given by,

$$sc_{x_i} = \frac{\boldsymbol{cen_{xi}}}{\sigma\left(x\right)} \tag{4}$$

such that $\sigma(scx_)$ equals 1.

Feature Extraction using Deep Convolution Neural Network

By retraining, CNNs may produce significant characteristics in terms of weight and threshold automatically. In this paper, a new CNN with dual conv_layer, single pool_layer, single smooth_layer, and full_connent_layerare presented for the categorization of heartbeats.

Figure 3. Deep CNN architecture based extraction

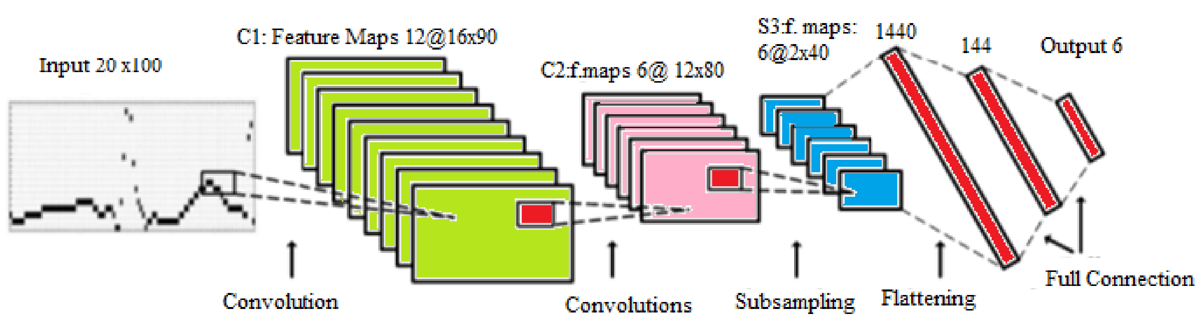


Figure 3 (Li et al., 2018) depicts the structural design and configuration of the projected CNN. Every convolutional layer in this network can be thought of as a fuzzy filter that improves the elements of the unique signal while falling noise. Every feature map has a convolution size of 2 × 11 and a stride of one. The greatest sub-sampling layer (i.e., the submixing layer) subsamples the signals using the restricted correlate concept, retaining crucial data while limiting the cost of data dimensions. The stride is two and the pooling size is two. The information in the pool_layer is altered to extracted features by the flatten_layer. In the single smooth_layer, the biassed dropout approach is used. Here, the activation function is found by rectifier linear unit (ReLU), the loss function was given by cross-entropy, and the adaptive learning rate method was the ADADELTA method.

Adaptive Learning Rate Method

By potentially setting the learning rate, the ADADELTA adaptive learning rate system was applied to the suggested CNN. The basis of the strategy is to accumulate the sum of squared incline above a window of historical slopes of a certain defined size, and this method uses a different information gain for each parameterization. The quadratic gradient's moving average E is derived:

$$E\left|g^2\right| = \rho.E\left|g\right|^2.t + \left(1-p\right).g_t^2 \tag{5}$$

Where g_t the gradient of the present time t and ρ is a decompose constant. Every iteration's value is calculated as follows:

$$\Delta x_t = -\frac{\sigma}{RMS[g]_t} \tag{6}$$

where σ is the training error that determines the size of a gradient step.

BIASED DROPOUT PROCESS

A biased dropout strategy was chosen for the proposed Deep CNN to minimize the rising training time. The activation level of the hidden state unit is utilized to obtain the benefits towards network performance with biased dropout. Generally, a hidden unit group's dropout rate is contrariwise correlated to its contributions to improving the network's performance. The maximum number of hidden units in a given hidden layer are separated into two groups based on their involvement in the beneficial value The dropout rate could be calculated below: where $p1$ denotes a low drop - out rate, whereas $p2$ denotes a high dropout rate.

$$p2 = c.p1\ (c>1) \tag{7}$$

The standard dropouts rate, p is calculated as follows:

$$p = \frac{(p1.n1 + p2.n2)}{n} \tag{8}$$

wherein $n1$ and $n2$ are the hidden layer unit numbers in every group, respectively. The Bernoulli distribution could be used to express the drop-out rates of a definite lth layer.

$$r^{(l)} = bernoulli(p) \tag{9}$$

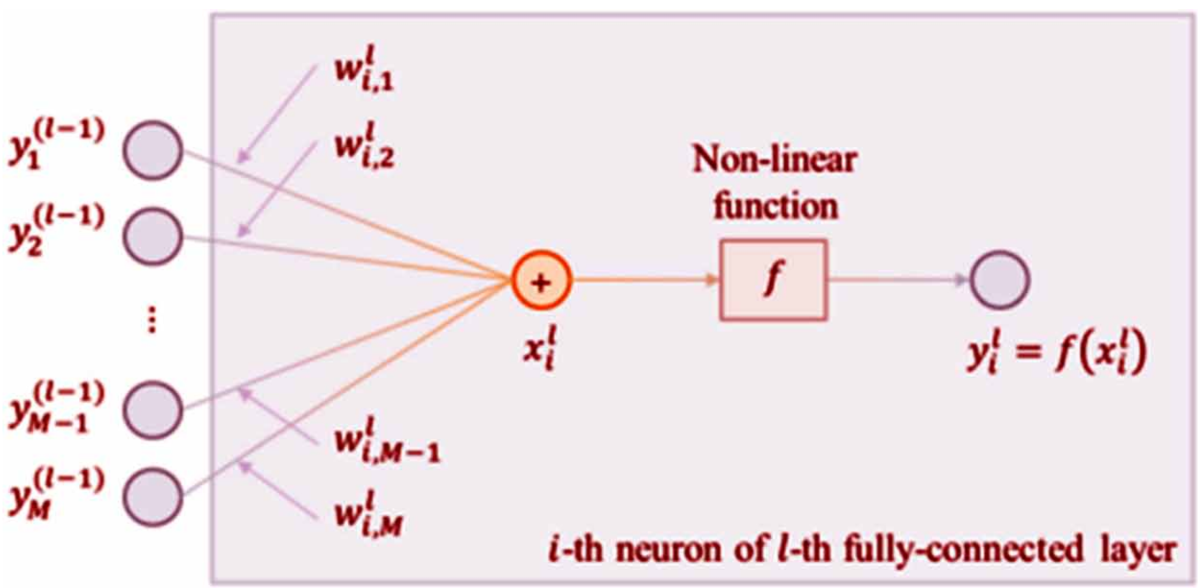
and upgrading of the lth layer's deep CNN result can be able to be expressed as

$$y'^{(l)} = r^{(l)} * y^{(l)} \tag{10}$$

$$z^{(l+1)} = w^{(l+1)} * y'^{(l)} + \propto^{(l+1)} \tag{11}$$

wherein $\boldsymbol{y}^{(l)}$ is the lth layer neuron output, $\boldsymbol{z}^{(l+1)}$ s the activation function input, $\boldsymbol{w}^{(l+1)}$ is the weight factor.

Figure 4. Biased dropout non-linearity function



This calculated the Pearson correlation coefficient whenever random samples were given to those layers to determine the extent of co-adaptation between the pre-nonlinearity installations. Due to the obvious CNN's weight pooling and local connectivity design, we discovered that neurons on the very same channel are associated with others in the convolutional layers, as seen in Figure 4 (Lee et al., 2020). We calculated the Pearson correlation coefficient whenever random samples were given to those layers to determine the extent of co-adaptation between the pre-nonlinearity installations. Due to the obvious CNN's weight pooling and local connectivity design, we discovered that neurons on the very same channel are associated with others in the convolutional layers, as seen in figure-4. If the weights Wc and Wd, j from the convolutional layer's channels such as c and d are independent, hence either two neurons on each channel, Xc and Xd, can be activated. As a result, the dropout across channels in CNNs can be functionally identical.

Pre-Training Process

These two networks seem to be fine-tuned using the Clarifai net and the VGG Net-D model. During the first convolutional layer, the Clarifai net uses a kernel of length 7×7 to filter the signals to acquire relevant data, which includes more contextual information, making it simpler to distinguish the signals but more difficult to switch partial occlusion. The VGG Net-D network uses a narrower 4×34 conv_ kernal to filter signals by getting hold of a restricted sequence, which contains a higher level of signal information to discuss the noise, but it lacks multilateral superiority. We investigate feature fusion to collect global and local information concurrently to discriminate more prominent signals in the network, resulting in improved performance, because all the layers in the network have a great capacity to unite the features and generalize well. With a maximum scale of 6 and a scaling factor of 0.8651, we create a pyramidal structure. owing to a connection input window of size 153×153, to identify the signals in the range of 32×28. We turn full_conv_layer into conv_layer and restructure layer settings due to the increased computational costs of the original sliding window method; then we use the full_conv network to handle input signals of random sizes. Every sliding window of width 5×5 at the fc6-Conv layer in the convolutional network equates to a detection window of size 153×224, on the original signal; the full_conv network may remove characteristics of all cluster centers but with only one forward iteration. As a result, the last pooling layer can be computed with numerous starting positions, each of which corresponds to a max-pooling map. Over the last pooling layer, we utilize max-pooling with a stride of 4; as a result, every input feature map incorporates 8 output feature maps.

To minimize partly cover with a stride out of 4 at the max_pool layer, we designate each starting point adjustment; there are only $(4 \times 4) = 16$ offsets present, specified as *Off*= (0,0), (1,0), (0,1), (1,1)}. For each offset *Off*(*o*= (*ox,oy*)Î*o*) , is considered as an input feature map, and hence single output feature map was produced, where *Off* is the position of beginning place at the top right on the input matrix for pooling. Beginning from the top left, offset max_pooling with kernel diameter of 2×2 and stride of 4 can produce output local features of dimensions 5×5, 2×3, 3×3, and 4×4 by beginning at the top left layer, correspondingly. And the four output feature maps above match the 25 detection windows of size 2×2 on the input feature map. However, in a standard pooling process, can be done on a single softmax layer of size 2×2 on the input matrix, which equates to just 5 detection windows of size 2×2. An original input map of size 7×7 can yield a feature map of the average size of 5, which corresponds to 25 exposure windows of size 3×3 on the input feature map, by applying max-pooling with a kernel size of 3×3 and stride of 1. As a result, our strategy is comparable to halving the stride length in order to conduct denser detection.

Feature Selection

Feature selection is a method of selecting a fraction of unique features while assessing the significance of the class label. The raw dataset can have a huge amount of characteristics and instances. To detect and delete irrelevant characteristics, feature selection is required. The goal of feature selection is to improve the accuracy rate. These approaches are divided into three groups. Filter approaches pick features using selective parameters that are mostly unaffected by classification. The second set of feature selection techniques is wrapped techniques. The significance of features is accurately observed by a model's predictive performance. The third category of feature selections is integrated techniques. The data-mining technique includes feature selection by default. These methods construct a decoder using all of the characteristics, then assess the classifier to determine the relevance of the variables. On the UCI cardiac arrhythmia dataset, we employed a variety of feature selection algorithms to minimize the dimensionality and find the three top dataset models.

Ensemble-Based Feature Selection Method

This section outlines how to classify arrhythmias using an ensemble method based on feature selection. The necessary phases are included in the Ensemble-based on Feature selection method: (1) Using the feature extraction technique, separate the original data into multiple subgroups. The result would have been more than multiple disjoint groups of features, (2) assessment of the accuracy rate of the subsets, (3) ensemble formation with voting, (4) a concatenated classifier assessment step employing quadruple data mining algorithms.

The following equation shows how to evaluate weight:

$$w_j = \left(e\left(c_j\right) - e\left(c_{j-1}\right)\right).\left(n - j\right) \tag{12}$$

where $e(c_j)$ is the training error of the c_j classification's training error acquired during the process of learning, and n represents the number of classifiers? The class labels for an occurrence are determined once the ensemble classifiers have indeed been constructed:

$$f\left(x\right) = arg\sum_{j=1}^{n} w_j c_j\left(x\right) \tag{13}$$

Complex Geometrical Features Denotation

To estimate characteristics from the observed Pulses, whether normal or arrhythmic, using the developed model, a valid time centre for each QRS complex must first be acquired. Using the emergence coordinates of the associated QRS complex, the absolute min and max indices of the extracted DWT dyadic scale, are computed. The optimal time centre of every identified QRS complex is found, as per exhaustive analyses completed which reaches the mean of the zero-crossing sites of the extracted DWT. To create a virtual close-up of each detected QRS complex, a rectangle with the following characteristics is created

- QRS complex is fiducially located at the rectangle's left-side mid-span.
- complex's actual range from the fiduciallytip is half the rectangle's elevation.
- time-centre of the QRS complex is located in the centre of the rectangle.
- range between the QRS time centre and its location is represented by the right-hand ordinate of the rectangle.

Following that, each QRS region and its matching DWT are treated as virtual pictures, with each being partitioned into 16 polar sectors. The curvature length of every extracted section is then calculated and is used as feature space components. In a window with length WL samples, the quantity curve-length of a theoretical time-series data, $x(t)$ can be approximated as:

$$M_{cl}(k) = \frac{1}{F_s} \sum_{t=k}^{k+w_{l-1}} \sqrt{1 + \left[x(t+1) - x(t) \right) F_s]} \tag{14}$$

where F_s is the time series' sampling frequency and x is the length of the instance series $x(t)$. The curve length can be used to determine the signal's duration, with x(t)events being either well-built or weak. The $M_{cl}(k)$ metric, in general, shows the level of sample flatness in the analysis window. Sharply elevated phases in the excerpted portion can be detected using this technique.

Proposed Bat Rider Optimization Algorithm (BROA)

The proposed BROA technique combines the multi-objective bat algorithm (MOBA) with the Rider Optimization Algorithm (ROA) by utilizing the bypassing rider's update rule with the assistance of ROA's updated formula. The suggested BaROA algorithm combines the advantages and disadvantages of MOBA and ROA, significantly, it achieves better convergence speed with a comprehensive optimal range and a larger predisposition toward the local optimal avoidance mechanism. On either side, good convergence rates ensure that the solutions are diverse, and BaROAs needed to cope with numerous objectives are beneficial. Generally, ROA is built on hypothetical principles and theories, which employs a novel computing platform known as fictitious rendering, which is a distinct calculating stage from artificial computing and nature-oriented systems. ROA is dependent on the riders' efficiency traits, which are divided into four categories: bypass, overtake, aggressor, and follower. Every rider has their personality, and they all want to get to their destination. The best rider is determined by a factor known as success rate, which should be as high as possible for the top or lead rider. Additionally, it is worth noting that under the fictional paradigm, ROA is the sole optimization. The most important aspect of ROA is that it renders the global optimum, which is nothing more than the classifier's connection weights. Furthermore, the locations of all the other four groups of riders are updated depending on the position of the lead rider, and the parameters required for upgrading the locations include the steering angle, accelerator, gear, etc. The location of the rider is updated based on the leader's location, and the optimization maintains them away from the local minimum avoidance of the tiny local region. The attacker is responsible for the attacker's capacity to perform local optimal evasion. On either side, ROA has a faster rate of convergence, which would be dependent on big global boundaries and the synchronization mechanism with effort. As a result, the locations are first updated in a randomized way in order to explore the environment. The overtake obtains the optimum search space, which is determined by the success rate and directional pointer, whereas the follower utilizes the locations with various dimensions to the lead rider. It's interesting to observe that the attacker's searching pace is boosted as a result of the multilayer search. Furthermore, ROA provides efficient findability. The capacity to switch the multi-objective function, on the other hand, is a huge question wherein the MOBA significantly contributes. As a result, combining the MOBA with the ROA allows for effective multi-objective handling. The echolocation of bats in identifying prey is the basis for MOBA. The algorithm phases of the suggested BaROA are as follows:

Step 1. Initialize the bat constrains
Step 2. Adjust the global best location *x*, as well as the ith bat's pulse duration, speed, and location as follows:

$$f_i = f_{min} + (f_{max} - f_{min})\beta,\ \beta\hat{\text{I}}[0,1] \tag{15}$$

$$v_i^{t+1} = v_i^t + \left(x_i^t + x'\right) f_i \tag{16}$$

$$x_t^{t+1} = x_i^t + v_i^t \tag{17}$$

$\boldsymbol{v_i^t}$ and $\boldsymbol{x_i^t}$ represent speed and location at time t, $\boldsymbol{v_i^{t+1}}$ and $\boldsymbol{x_t^{t+1}}$ represent positions and velocities at time t + 1, and β is a randomized value between 0 and 1 and 1.

Step 3. The following equation generates a new solution for the bat if the random number is bigger than r_i.

$$x_{new} = x_{old} + \hat{\text{I}}\, A^t \tag{18}$$

where Î is a random number, ε Î [− 1, 1], and A^t stand for the average quantity of all bats at instant t.

Step 4. The new solution is approved if the random number is less than A_i and $F(x_i) < F(x^*)$. Then, update A_i and r_i, correspondingly.

$$A_i^{t+1} = \alpha A_i^t \tag{19}$$

$$r_i^t = r_i^0 \left[1 - e^{-yt}\right] \tag{20}$$

where $A_i^{t+1} =$ and A_i^t denote the loudness at times t and t + 1, respectively; r_i^0 and r_i^t are the early pulse speed and pulse rate at instance t, correspondingly, α is a constant parameter in the range [0, 1], γ is a stable constraint, and $\gamma>0$

Step 5. Arrange the bats by fitness level and consider the current best solution x*
Step 6. Repeat Step 2 till the maximum number of generations has been achieved, and then produce the globally optimal.

Depending on the exact optimal solution, the penalty constraint's value should be as maximum. The impact of the objective function is negligible when the inequality constraints are satisfied. A reasonable number for the weights and biases is known to offer a compromise on the algorithm's global and local exploration abilities. It was deduced that the device should begin with high weights and biases for global exploration, and hence it should decrease in subsequent rounds to allow for finer local explorations. The parameter provided by a concave function, on the other hand, will dramatically speed the convergence rate, causing the algorithm to drop into a local optimal. Regarding the best algorithm, there is some operator in the iterations that outperforms the others. As a result, by picking the proper operators at different periods, the algorithm's global search capabilities can be boosted even more.

Classification of Detected Signals using Deep CNN_BROA

Convolution map: The convolution operation is a fundamental element in CNN, and its goal is to identify and extract data. However, in CPU-based models, it's being used to refine the derived feature using R-peak analysis. It is made up of a collection of learnable square filters that aid in the identification of acceptable feature sets. Every filtering is employed to the ECG signal's raw data.

Max-pooling map: Convolution layers are separated by sub-sampling layers in the proposed CNN architecture, and operate as a unique extracting features strategy. Although a layer of max-pooling can be utilized instead of feature selection, we applied optimization approaches separately in this study to boost the probability of feature originality by employing the ROA as an optimization strategy. The trained model receives the output of the max_pool_layer, which contains the highest activation rate to construct the structural model.

The operation of the ReLu layer is to improve the speed while training happens, hence neglecting the issue of gradient function. This layer is protected with improved specifications for better classification of heart disease by observing the ECG signal. The Categorization model named Heartbeats Categorization Model (HCM) is cinched with the suggested Convolutional Neural Network (CNN) for better accuracy.

In multiclass classification, the cross-entropy loss function is commonly utilized. The formula is as follows:

$$L_i = -\left[y_i log\ y_i^{'} + \left(1 - y_i\right) log\left(1 - y_i^{'}\right)\right] \tag{21}$$

where y_i is the anticipated likelihood and $y_i^{'}$ is the label During training, in each instance samples from a batch are supplied to the network, and the average score of the batch's loss is called the batch's loss. Owing to its simplicity, it is unable to distinguish between losses from distinct samples in a batch during training and so enhances the accuracy rate further. A batch sample's loss is arranged in descending order, with the highest values being averaged as the final loss. Throughout the training, it emphasizes ambiguous data with large loss values and enhances classification accuracy toward those.

EXPERIMENTAL ANALYSIS

For the arrithyima forecast, the outcomes and discussion of the suggested deep CNN_BROA network are used and we assess the success with various performance metrics. Finally, there is an experiment to equate the efficiency of the proposed model with other applications of deep learning. Using measurement metrics such as accuracy, sensitivity, specificity, and F1-score to assess the effectiveness of the proposed system. accuracy is the proportion of overall subjects accurately identified.

$$Accuracy = \frac{\sum TP + \sum TN}{\sum TP + \sum TN + \sum FP + \sum FN} \tag{22}$$

The number of patients with cardiac arrest is sensitive.

$$Sensitivity = \frac{\sum TP}{\sum TP + \sum FN} \tag{23}$$

Specificity is the percentage of individuals who have no negative illness. The recall is the same as specificity.

$$Specificity = \frac{\sum TN}{\sum TN + \sum FP} \tag{24}$$

A harmonic means of accuracy and recall is F1-Score. These are

$$F1 - Score = \frac{2 \times Recall \times Precision}{Recall \times Precision} \tag{25}$$

where TP and FP represent the correct and incorrect classification of cardiac arrest subjects. Similarly, TN and FN denote the percentage of subjects not possessing cardiac arrest who are correctly and incorrectly listed, respectively. Table 1 shows the proposed deep CNN_BROA network model performance with different performance metrics and its data on training and testing. The metrics used for evaluation are accuracy, Specificity, Sensitivity, and F1-Score.

Table 1. Performance of deep CNN_BROA network for 100 epoch size

Performance Metrics	Data	
	Testing (%)	Training (%)
Accuracy	94	89
Specificity	98	91
Sensitivity	94	82
F1-Score	90	84

Figure 5. Comparison of training and testing model for 100 epochs

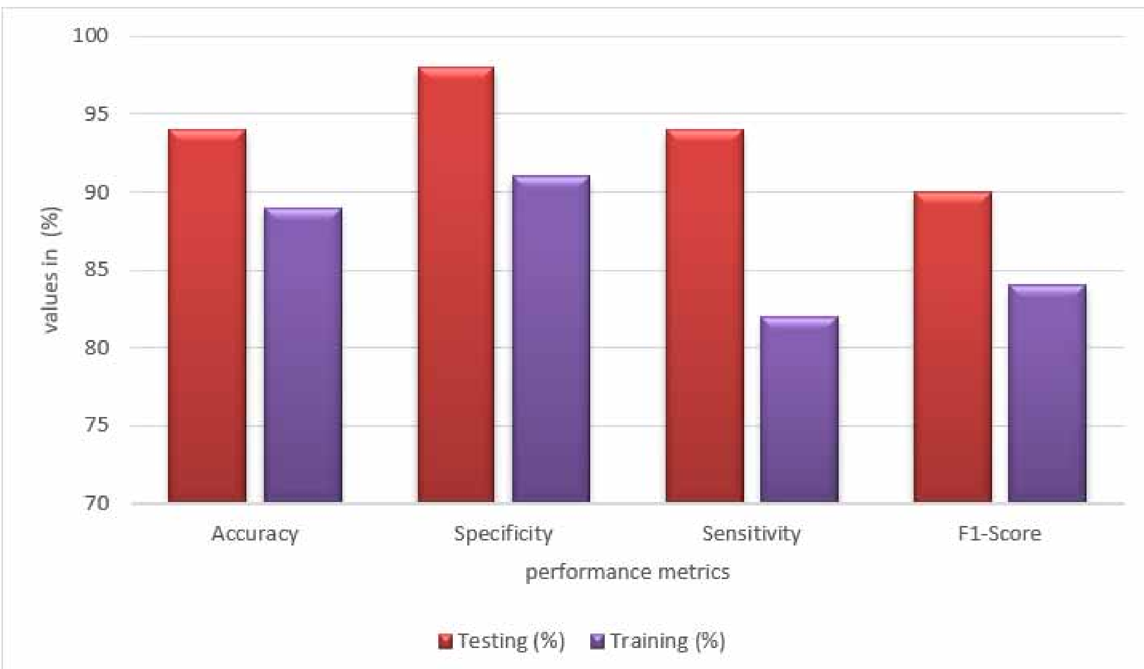


Figure 5 shows the proposed deep CNN_BROA network training and testing model for 100 epochs. The X-axis represents performance metrics and Y-axis represents values obtained. The blue color indicates the testing data and the maroon indicates the training data. The proposed deep CNN_BROA network model achieves 94% and 89% of testing and training accuracy, 98% and 91% of testing and training specificity, 94% and 82% of testing and training sensitivity, 90% and 84% of testing and training F1-score

Table 2. Performance of deep CNN_BROA network for epoch size=200 and 300

Performance Metrics	Epochs=200		Epochs=300	
	Testing (%)	Training (%)	Testing (%)	Training (%)
Accuracy	94	80	97	84
Specificity	93	84	93	82
Sensitivity	96	87	95	81
F1-Score	93	84	92	85

Figure 6. Comparison of training and testing model for 200 epochs

Figure 6 shows the proposed deep CNN_BROA network training and testing model for 200 epochs. The X-axis represents performance metrics and Y-axis represents values obtained. The blue color indicates the testing data and the maroon indicates the training data. The proposed deep CNN_BROA network model achieves 94% and 80% of testing and training accuracy, 93% and 84% of testing and training specificity, 96% and 87% of testing and training sensitivity, and 93% and 84% of testing and training F1-score.

Figure 7. Comparison of training and testing model for 300 epochs

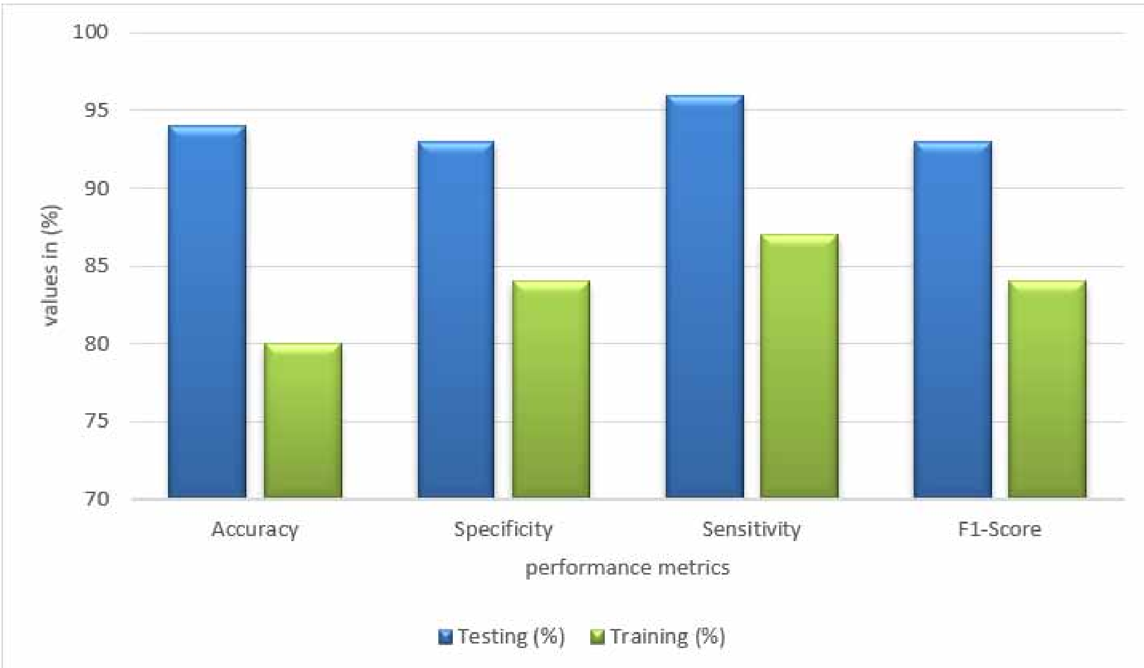


Figure 7 shows the proposed deep CNN_BROA network training and testing model for 300 epochs. The X-axis represents performance metrics and Y-axis represents values obtained. The blue color indicates the testing data and the maroon indicates the training data. The proposed deep CNN_BROA network model achieves 97% and 84% of testing and training accuracy, 93% and 82% of testing and training specificity, 95% and 81% of testing and training sensitivity, and 92% and 85% of testing and training F1-score.

CONCLUSION

The suggested deep convolutional neural network with Bat-Rider optimized Classification Phase (deep CNN BROA) is used in this paper to provide an autonomous technique for arrhythmia classification. The ECG data are first input into the feature extraction module, which extracts the features that correlate to the pulses. The chosen characteristics are sent into the arrhythmia classification algorithm, which categorizes the patient as having an arrhythmia or being normal. Deep CNN is a classifier that provides accurate categorization and is completely automated. The suggested BROA's advantage in training the classifier is classification accuracy. The experiment is carried out with the help of the MIT-BIH Arrhythmia Database, and the study is premised on the assessment metrics. The maximum values of the suggested arrhythmia classification algorithm were obtained as 97%, 96%, 94%, and 95%, for accuracy, sensitivity, specificity, and F1-score respectively. The future work concentrates on the need for research in the areas of security and privacy issues related to technologies used for cardiac arrest prediction developments. Furthermore, technology should be utilized to assist and motivate frontline healthcare practitioners and officials in the fight against cardiac arrest.

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Chapter 5
Computer-Assistive Techniques for Monitoring and Tracking Patient Healthcare and Engagement

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ABSTRACT

Assistive devices and technology reduce a person's dependency on others while also improving the overall quality. Wheelchairs, visual aids, hearing aids, and specialist computer software and hardware systems help the elderly and disabled improve their hearing, vision, mobility, and communication. Assistive technology, for example, provides enormous opportunity to improve the effectiveness of both health and social care delivery. 'Low-tech' products like memory aides and digital calendars, as well as 'high-tech' items like health tracking gadgets and wearables, are examples of assistive technologies. Assistive devices can be used to improve quality of life, improve lifestyle, and boost independence, depending on the type of device. Patient and caregiver acceptance of technology is influenced by a variety of factors, including perceived skills and competencies in utilizing the device, expectancies, trust, and reliability.

1. INTRODUCTION

Many scientific domains are strongly connected, and each health specialty is relying on the work of others. Academics, researchers, and practitioners, on the other hand, are frequently constrained to their

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chambers of knowledge, language, and expertise. The prevailing availability of knowledge strangely magnifies this problem; massive quantities of big data and the cloud era have helped short-term study in a variety of fields. When it comes to assisting persons with limited mobility, poor cognitive capacity, or chronic illnesses that cause dependency, the connection between a smart environment, assistive robots, and the user is very significant, (Ktistakis, Goodman, et al., 2022). To ensure that robotic care and rehabilitation systems work properly, a system must be developed that ensures interactions between the patient, caregiver, assistive robots, and the IoT environment.

Assistive technology, according to the World Health Organization, is an umbrella word that encompasses all systems and services connected to the delivery of assistive products and services. Assistive technology facilitates elderly people's desire to age in place and enhances their quality of life, allowing them and their caregivers to improve their quality of life (Ktistakis, Goodman, et al., 2022), (Pugliese, Sala, et. al., 2022). Assistive technology needs to be usable and inexpensive to meet the goal of being produced in a highly accessible, compassionate, and ethical manner. This type of interaction is especially important for patients with special needs since it can help them enhance their quality of life dramatically (Pugliese, Sala, et. al., 2022), (Dratsiou, Varella, et. al., 2022). However, depending on the user's needs, multiple means of regulating the environment are required.

Given the aging population in developed countries, mobility assistance will become increasingly important. The employment of real-world trials – with actual users and real environments – to test the validity and suitability of assistive technology is a significant step forward in their implementation (Pugliese, Sala, et. al., 2022), (Dratsiou, Varella, et. al., 2022). In this discipline, the application of Agent Technology is enabling new forms of engagement and generating new solutions. The ultimate goal of the interaction between robots, Agent Systems, and users is to increase autonomy while also improving the quality and complexity of services provided. Agent Systems' adaptability and learning skills meet the needs of a community of users with a changing set of wants and profiles. Over time nonetheless, some critical issues like safety and security have been raised. The portion of the world's population aged 60 and up is the fastest expanding due to low birth rates and rising life expectancy (Anaya, Zhan, et. al. 2021).

More than one billion people, according to the WHO, require assistive technology. With a growing worldwide population and an increase in non-communicable diseases, this figure is expected to exceed two billion by 2050, with many older people requiring two or more items. There are expected to be 2 billion people in need of assistive devices by 2050, with only one in every 20 people having access to them. Like its predecessor, the WHO Priority Assistive Items List (APL), the new WHO Priority Assistive Products List (APL) will be a crucial instrument in making these products accessible to an aging population and people with disabilities all over the world.

This chapter uses smart wheelchairs as a case study to present an Internet of things framework for assistive mobility devices that incorporates latency and security, as well as a multi-sensor fusion pipeline for improved autonomous navigation. Future assistive technology solutions should be evaluated for satisfaction, medical contribution, and cost-effectiveness, among other factors (Anaya, Zhan, et. al. 2021), (Hachaj, Ogiela, et. al. 2015). Assistive technologies should be included in this concept of smart aging, which is a comprehensive and multidisciplinary approach to senior adults that are tailored to each individual. For elderly individuals, the ultimate purpose of assistive technology should be to improve their quality of life. (Hachaj, Ogiela, et. al. 2015).

Figure 1. Concomitance of assistive technology

1.1 Assistive Technology Monitoring and Tracking Patient Healthcare

The number of gadgets that are connected to the internet has increased dramatically. Assistive Technology is a broad term in the field of healthcare monitoring that encompasses assistive, adaptive, and rehabilitative equipment for persons with impairments, as well as the procedures for selecting, locating, and using them (Sander, Oxlund,et. al., 2015). Given recent developments in medical science and Artificial Intelligence, robots have the potential to support and aid humans in a variety of scenarios, including homes, businesses, schools, and more (AI). One example of science in action is healthcare, which is not a new notion.

This chapter provides an overview of nonsurgical robots used to support healthcare workers, such as nurses, caregivers, and therapists. This section has described the following techniques:

1.1.1. Hospital Robots

The company has rapidly shown an increased interest in developing robots to assist nurses in hospitals and clinics. The robotic nursing assistants are programmed to follow the orders of a nurse (Ranney, Griffeth, et. al. 2020). A robotic nursing assistant will work alongside nurses, assisting them with non-essential tasks like retrieving supplies, allowing nurses to focus on more crucial tasks like patient care. Due to a lack of personal protective equipment, the COVID-19 outbreak also revealed how vulnerable nurses are. In the event of a pandemic, robots, on the other hand, are resistant to viruses and other germs and can assist. In recent years, a variety of commercially available robots have been deployed in hospitals to help with transportation tasks.

Figure 2. The Moxi Robot gathering supplies[12]

1.1.2. Care Robots

Care Robot, as a robot, can only be identified by the purpose for which it is used, namely, to provide or support people in the process of patient care. As a result, this ambiguous term might encompass a wide range of robots with varying hardware specs and capabilities. The vast majority of Care Robot applications and surveys are geared toward surveillance and trying to assist seniors both psychically (reminding, assisting mentally, empowering, etc.) and biologically (trying to hand around artifacts, trying to deliver products, or helping in eateries), as well as able to diagnose and support in the education of children with mental disorders like autism. (Ranney, Griffeth, et. al., 2020)

Softbank Robotics (formerly Aldebaran Robotics) developed Pepper and Nao, social robots that could be utilized in healthcare (Ranney, Griffeth, et. al., 2020). Pepper is a four-foot semi-humanoid robot with sonar, laser, and bumper sensors mounted on a wheeled base (rather than legs). Pepper has served as a teaching assistant for children, a companion for the elderly, and a coach for older people with psychiatric diseases while they participate in fun rehabilitation activities (Bevölkerung, Fakten, et. al. 2008).

Figure 3. Pepper Robot[13]

1.1.3. Walking Assisting Technology

Walking helpers are developed to assist people with poor walking ability in their daily activities and provide additional support. Different types of walking aids can be adapted depending on the amount of disability (Bevölkerung, Fakten, et. al. 2008). People with complete paralysis from a spinal cord injury or traumatic brain injury, for example, may benefit from an intelligent wheelchair, whereas people with a feeble lower limb from a stroke or an accident can benefit from a wearable exoskeleton that can aid rehabilitation and recovery.

Figure 4. Walker frame-based walking Assistant[16]

1.1.4. Care-O-Bolt

Care-O-Bot is a Fraunhofer service robot that can be used in a variety of circumstances and tasks, including as a mobile information center, an item collecting and delivery tool, and a security or surveillance tool (Jacobs, Graf, et. al. 2012). Because of its open-source software interfaces, it can also be used as a research platform. As depicted in Figure 5, it consists of an omnidirectional platform, a torso with a sensor ring above it, and ahead with a touch screen. It also gives the option of having zero to two gripping arms. The most essential characteristic of Care-O-Bot 4 is its hardware adaptability and agility, which are achieved through the use of spherical joints (Jacobs, Graf, et. al. 2012), (Dagiogloi, Konstantopoulos, et. al. 2014).

Figure 5. Care-O-Bot[18]

2. COMPUTING ASSISTIVE TECHNIQUES FOR MONITORING CARDIAC PATIENTS

Heart failure is a prominent disease in the old and middle ages, and it is one of the top causes of death all over the world. Coronary Artery Disease (CAD), in particular, is a common cardiovascular disease with a high mortality rate. Physicians advocate clinical diagnosis procedures such as angiography since it is the best diagnosis for CAD. Today, hospitals and practitioners have significant challenges in accurately predicting and diagnosing this disease. Computing technological improvements have aided healthcare facilities in collecting and storing the data for clinical decision-making. In many modern countries, hospitals gather and retain patient data in a computerized and comprehensible format. Coronary heart disease (CHD) is a proven serious public health problem that affects people all over the world.

(Khan, Y., Qamar, U et. al. 2019) found that some research has focused on achieving the highest accuracies by proposing extremely reliable and efficient techniques, such as GA with SVM for over 98% accuracy, PCA and SVM for over 99% accuracy, PCA for over 98% accuracy, and a collaborative bagged decision trees for around 99% accuracy. Furthermore, when it is a question of life, accuracy is the most important aspect and since machines are used to do that prediction, the margin of error should be as little as possible.

Cardiovascular diseases (CVDs) are the most common cause of death around the world. CVDs took the lives of 17.9 million people worldwide in 2019, accounting for 32% of all deaths. Heart attacks and strokes were responsible for 85 percent of these deaths. CVDs were responsible for 38 percent of the 17 million premature deaths (before the age of 70) caused by noncommunicable diseases in 2019. The majority of cardiovascular illnesses can be avoided by addressing behavioral risk factors such as consumption of tobacco, poor diet and obesity, lack of physical activity, and heavy alcohol consumption. It's critical to recognize the cardiovascular illness as soon as possible so that treatment may begin with counseling and medications.

An ECG is the most commonly used test for heart arrhythmia. The ECG uses electrodes on the skin's surface to measure the electrical pulses of the heart. A conventional resting ECG, on the other hand, can only provide a snapshot of the patient's cardiovascular activity in real-time, making it impossible to diagnose many arrhythmias. Because an intermittent arrhythmia can go undetected, doctors must rely on self-monitoring and symptoms stated by patients to make a final diagnosis. In some cases, ambulatory ECG data may be collected for extended periods in an attempt to obtain data during the occurrence of an intermittent arrhythmia.

(Joseph J. Oresko, et.al 2010) proposed smartphone-based platform technologies for wearable CVD diagnosis that can capture and show real-time ECGs, extract features, and identify beats. Two smartphone-based solutions for continuous ECG signal monitoring and recording effectively diagnose CVD in real-time and provide customized cardiac health summary reports. It not only records the ECG signal to be stored for offline analysis, just like with Holter monitors but also provides the user a more advanced interface with real-time CVD tracking. The machine-learning platform diagnoses right bundle branch block (RBBB), PVC, paced beat (PACE), and PFUS beats, whereas the plug-in-based platform currently diagnoses PVC beats, which is an exceptionally common arrhythmia. Users can use these platforms to conduct assistive diagnosis tasks including establishing a baseline or irregular beats. They can also use the system to track their daily number of abnormal beats and see if they can reduce the number of uncomfortable and potentially harmful arrhythmic beats by changing their lifestyle, such as boosting their exercise, regulating their food, limiting caffeine intake, and so on.

According to epidemiology, these anomalies can be found in 2–15 percent of the nondiabetic overall population and are strongly and persistently linked to high blood pressure. Although there is evidence of a link between retinal microvascular abnormalities and stroke, there is no clear evidence of a separate or direct link between atherosclerosis, heart disease, or cardiovascular mortality. To indicate the existence and intensity of retinal arteriolar constriction and other microvascular features, new computer-based imaging approaches are currently being developed. Retinal microvascular anomalies may be helpful as risk indicators for cerebrovascular disorders if they can be properly quantified. (Wong, Klein et. al. 2001). Patients with heart failure may be able to do successful self-care with the help of mobile health. The creation and beta testing of a mobile application intervention to enhance self-care and increase symptom awareness in community-dwelling patients with heart failure were described in this article. The outcomes of two validated measures, the Self-care of Heart Failure Index and the Heart Failure Somatic Awareness Scale, were compared using t-tests before and after the intervention (Foster M. et. al. 2018)

3. LIFE CYCLE MODEL

A proposed unified framework supporting digital health is One Digital Health. The One Digital framework study is premised on 2 key factors i.e., One Health and Digital health, 3 outlooks i.e., Individual wellness, population & community, along with the ecosystem, sub-dimensions (citizens' involvement, education, ecosystem, veterinary, and human health care industry) (Bevölkerung, Fakten, et. al. 2008).

One Health and Digital Health aspires to electronically alter future healthcare systems through the implementation of a holistic healthcare sciences approach that addresses broad digitalization perspectives on human health, veterinary care, and environmental conservation. This method is used to assess how subsequent generations of health informaticians will cope with the increased variability of healthcare systems in technologically changed health environments (Jacobs, Graf, et. al. 2012), (Dagiogloi, Konstantopoulos, et. al. 2014). Individuals and their medical information have been asked to perform key roles in the improvement of person and population perspective information in the emerging hybrid environment.

The framework's key difficulties include supporting and enhancing contact between one health & digital health. To facilitate suggested strategies and the implementation of real-time, info contributions in pharmacology & environment, one health & digital health group are working together. Digital health education and awareness, on the other hand, are important in holistic, global health and data science research. i.e, the ability to comprehend and participate in health promotion and prevention activities, self-management, and participation in the prevention, management, and relief of possible problems are required. As a result, individuals in a healthy One Digital Health system should take proactive measures to prevent and react to medical calamities, such as the COVID-19 pandemic.

3.1 Understanding 2 Key Factors: "One Health" and "Digital Health"

Many researchers have contributed to the advancement of fundamental ideas of health info systems. Increasing adoption of technology and efficiency, improving technological security, quality, and performance, and boosting care efficiency are only a few examples of such contributions. Researchers in the domains of one health and digital health (Dagiogloi, Konstantopoulos, et. al. 2014) are working in zones more extensively by examining research subjects that are continually improving due to advances in health informatics (Dagiogloi, Konstantopoulos, et. al. 2014).

The importance of customer medical informatics in the twenty-first century has been highlighted strongly by eHealth. Over the last two decades, eHealth concepts have been defined and propagated. Despite this, the tremendous process of digitizing health care (which we are experiencing today) has refocused attention on economics. The term "digital health" was coined to reflect this approach (Dagiogloi, Konstantopoulos, et. al. 2014), (Wang, Su, and Li, et. al. 2021).

In other words, there appear to be no significant differences between e-Health and digital health, as there are no archetype shifts. Digital health, on the other hand, might be considered a developed version of eHealth, because it exclusively accounts for the implementation of health info and assistive decision tools via digitized technology in a context that includes living and environment components. As a result, digital health entails:

(1) Handling data & information in an omnipresent manner to proficiently manage healthcare
(2) Reforming the medical field and pharmaceutics more personalized & accurate (Wang, Su, and Li, et. al. 2021).
(3) Looking out for goals associated with health advancement, patients healthcare, and effective self-management; and
(4) Taking into account the financial statement of the services volunteered. (Wang, Su, and Li, et. al. 2021).

Medical practitioners & research scientists in the domains of technology, healthcare, health financials, and information management are needed to apply digital health treatments. For these reasons, we refer to "digital health" rather than "eHealth' ' (Wang, Su, and Li, et. al. 2021). The collaborative, multi-sectoral, and multiple disciplinary approaches of One Health practitioners are based on healthcare, well-being, individuals, demographic, and bio-systems. By recognizing the links between humans, animals, plants, and their ecosystems. At the neighborhood, provincial, national, and global levels, One Health practitioners seek to achieve the best health and well-being outcomes.

These current disciplines attempt to increase public knowledge on risks related to health, its management policies & decisions. One Health informatics has been presented as a way to integrate various study subjects throughout global health and life sciences study in this vein (Vest, Gamm., et. al. 2010). One Health informatics' main themes are using big data analytics to support and improve public health and medical research, as well as addressing issues like biodiversity control, disaster management, and disease monitoring.

3.2. Ternary Perspectives: "Individual Well Being-Population-Ecosystem

The Lifecycle model's second layer examines how the concept of "individual" is recognized inside the concept of "population" (i.e., without discriminating between humans and wildlife), the way a population affects and communicates with an ecosystem, as well as the way ecosystem response backs.

3.2.1. *Individual Health and Wellbeing*

The growing recognition of similar dangers faced by humans and wildlife opens up possibilities for generating new information and knowledge by harnessing enormous volumes of previously untapped data sources on zoonoses (Vest, Gamm., et. al. 2010). The lifecycle mission includes advancing faster and more reliable approaches for detecting disease trends, outbreaks, infections, and emergent causes. The critical relevance of gathering digital health data to improve our understanding underscores the need for platforms and technologies that facilitate and acknowledge the transition from big to smart data. Smart data entails novel techniques that are required to address critical questions in the health sector. To address these problems, new ecosystem-driven paradigms and transformational technologies are required.

3.2.2. *Population and Society*

Providing a generalization of concepts connected to customized healthcare coverage and well-being is not the same as discussing demographics and their societal organization. Although we're talking about individual-level, predictive, tailored, preventative, and collaborative health care, moving on to population-level, holistic viewpoints necessitates taking into account individual variances (Vest, Gamm., et. al. 2010), (Haux, R.,et. al. 2010). Personalized health, as opposed to a one-size-fits-all strategy, must account for an individual's heterogeneity in terms of genes, settings, digital health knowledge, choices, and behaviors.

This necessitates the systematic integration of knowledge into unique decision-making processes. Decisions about the prevention and control of all threats and risks to public health are part of these procedures.

3.2.3. *Ecosystem*

The term environment refers to the consideration of all living and nonliving entities in an ecosystem. This takes into account topics such as biodiversity conservation and the close ties that exist between the health, care, and well-being of all components in a given ecosystem. Controlling and governing sustainable development is best accomplished by evaluating ecosystem services, which are competent in measuring and evaluating all of the products or services produced within ecosystems.

Digital technologies such as (1) environmental monitoring and management knowledge management; (2) automated and scalable approaches for collecting, digitizing, and assembling geo-coded large amounts of data; and (3) information-fusion algorithms that use massive datasets and clinical data have recently been added to such networks.

As a result, the environment appears to be "digitized" in ecosystems that include animals and people, as well as software and machines, as independent and communicating entities to improve decision making. The deployment of a digital ecosystem aims to improve communication efficiency while reducing people's reliance on centralized or dispersed control dynamics. Common substrates of data and knowledge that are now reachable, accessible, and ready to be examined in fresh and innovative ways are the source of such digital biodiversity (Vest, Gamm., et. al. 2010), (Haux, R.,et. al. 2010).

However, this places us in a situation, which is necessary for developing appropriate digital solutions (i.e., techniques for preserving digital biodiversity) based on people's intelligence and logic. Such solutions are preferable to those obtained through the use of standard artificial intelligence.

3.3 The Five Facets: Education- Citizen's Engagement- Health Care Industry- Human and Industry

3.3.1. Education

The model should not be confined to the research and development area of health-related university education. Curriculums at all levels and disciplines must teach basic and cross-disciplinary knowledge and understanding of health and its digitization. The model is much more than a framework of data management which is a general scenario (Vest, Gamm., et. al. 2010), (Haux, R.,et. al. 2010). It provides citizens with educational opportunities so that they would secure and manage their private information when they publish it on social media.

The upcoming generation of academics and researchers will be participating in reframing important turning points for incorporating new knowledge into the designed model, as well as continuously upgrading the underpinning philosophy and technological, and regulated consequences. Because of its complicated nature, fully appreciating the life cycle model perspective is difficult. As a result, scientists, practitioners, and people must collaborate to develop sound health and well-being implications. The issues of the model are:

(1) developing a comprehensive and interspersed understanding of human and animal health and wellness in shared ecology, and (Agarwal, Gao & DesRoches, et. al. 2010)
(2) determining how digitized technologies support and enhance human & animal health and wellness. (Agarwal, Gao & DesRoches, et. al. 2010)

3.3.2. Citizen's Engagement

Citizens who trust health care delivery must have the ability to use digital health data to control an individual's health and personal info. Patient participation, direct advantages for application end-users, and management organizations all influence the usage of implemented opportunities (Mantas, Ammenwerth & Demiris et. al., 2010). Smart towns and communities (i.ecities and communities that make heavy use of cellphones that can geolocate people and follow their movements) can be intrusive data sources.

Invasive methodologies employed during pandemic outbreaks, on the other hand, assist health practitioners and decision-makers in determining how to build suitable policies based on factual and relatively close data in situations of force majeure. As a result, policymakers may choose to proactively indulge the public by permitting the usage & assessment of information on a personal level, mass level for both (human & animal) contact & access to specific facilities (Mantas, Ammenwerth & Demiris et. al., 2010). This will entail allowing individuals to participate in the development of complicated policies over time (for example, policies relating to ethics, legislation, big data judgments, and the molding of social norms).

3.3.3. Health Care Industry

By measuring public health implications, monitoring human & animal health, and undertaking risk and assistive management workflows, the designed model hopes to answer difficult concerns about disease follow-ups (Mantas, Ammenwerth & Demiris et. al., 2010). Health-care delivery providers have recently shifted their focus to offering facilities to groups of patients. The digital reforms of animal health care systems are accelerated by rapid diagnosis and treatment of health care clients, effective service supply, and continual improvement in care quality (Cincotti, Mattia, Aloise, et. al. 2008).

Patients (including human and animal patients) can now be assessed using dynamic methodologies that incorporate data formed by patient's participation, thanks to digitalization and the growing use of smartphones & omnipresent health apps (Cincotti, Mattia, Aloise, et. al. 2008). Preventive advice and predictive alarm systems are two examples of individualized health care services enhanced by these technologies.

3.3.4. Human and Industry

Pharma service providers and policyholders, equipment and pharma product manufacturers, pharma transporters, and maintenance providers, regulating firms and standardization organizations, health care customers, sick people, and caretakers make up the human and animal health care system (Zilz, Pang, et. al. 2021). Digitalization and interconnection, which form the base of new paradigms, are driving the whole healthcare industry.

Managing, gathering, preserving, archiving, and analyzing a variety of real data readily accessible either by the organization or any linked system is among the primary problems of the new healthcare architecture (Zilz, Pang, et. al. 2021). The current industrial revolution's (i.eIndustry 4.0) main aim is to upgrade automatic systems and connect stability by enhancing system interoperability and enabling decentralized, real-time generated data collecting and storage.

3.3.5. Environment

In everyday conditions or disturbing circumstances, such as toxic chemical incidents or catastrophes, environmental monitoring is a vital component of neighborhood management (Zilz, Pang, et. al. 2021). The digital landscape has enabled the implementation of hypothetical and experimentally breakthroughs in automation and AI.

The "human-nature-pollution" link and its function in an upgraded urban framework must be addressed while addressing the environmental aspect of the model. People in high-density metropolitan regions are increasingly adopting technological platforms to report unexpected incidents, resulting in increased citizen participation (Smith, Hernandez & Ebuenyi, et. al. 2020). Furthermore, these individuals are increasingly employing green technology, which helps to mitigate the detrimental effects of specific acts on human health and the environment.

This ecological change, according to the model, entails more than the use of cellphone and IoT for behavioral, well-being, and health management. This transformation is a result of the Industry revolution 4.0, which intends to make it easier for community members to connect with complex yet simple digitized frameworks (Smith, Hernandez & Ebuenyi, et. al. 2020). The revolution, on the other hand, has several challenges, most of which are connected to costs for development, monitoring, implementation & maintenance costs, and user expectations.

Figure 6. Lifecycle model of Computer Assistive technology for patient's healthcare and management

4. APPLICATIONS OF ASSISTIVE TECHNOLOGIES

With the advancement in innovation, science, and the medical care industry numerous effective applications were sent off in reality and with time they were exceptionally acknowledged by patients and specialists. These strategies and gadgets were overhauled with input and innovative upgrades. Different uses of computer assistive applications are as per the following:

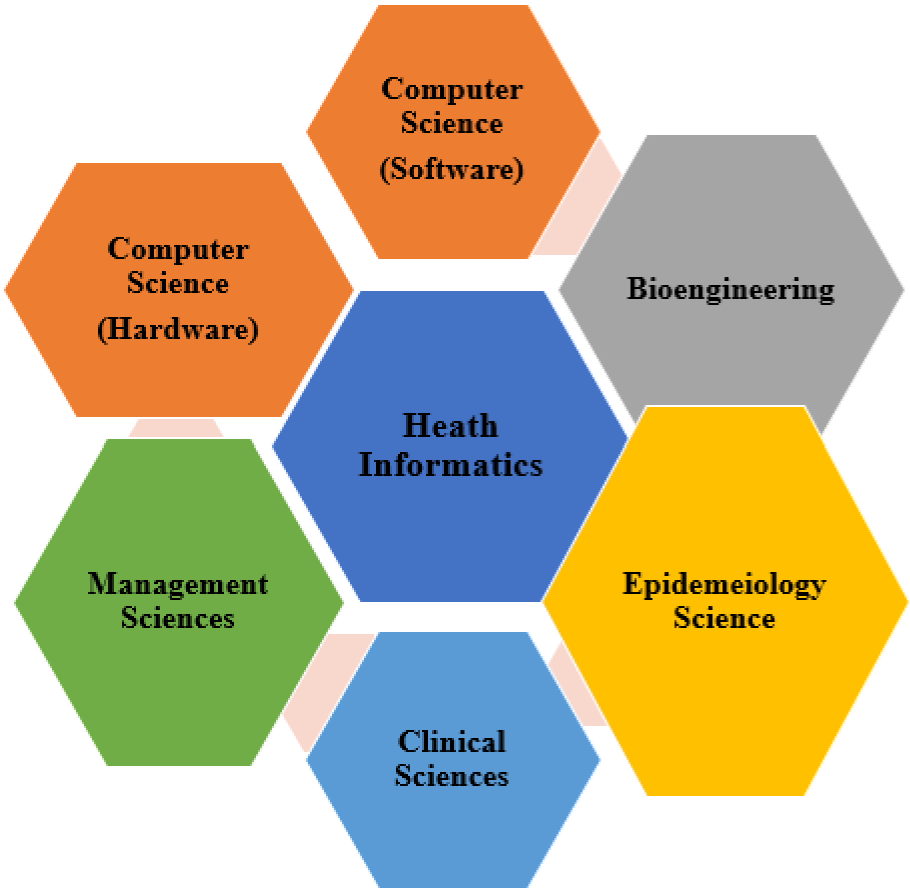
4.1. Medical Informatics

Clinical Informatics is concerned with the acquisition, storage, and use of data for health and biomedical specialists and patients to benefit from what others have accomplished and learned (Smith, Hernandez & Ebuenyi, et. al. 2020). It compiles data that can be used to determine patterns or examples of disease processes, as well as diagnostic tests and treatments. It promotes health by involving caring professionals in the decision-making process for patient consideration outcomes.

Clinical Informatics improves and streamlines communication between healthcare disciplines (Jutai, Tuazon, et. al. 2021). As a consequence of Medical Informatics, health record-keeping on PCs allows for clear and quicker access to patient narratives. Clinical and well-being informatics is an interdisciplinary field that includes:

- Informatics
- Decision support systems
- Telemedicine
- Customer wellbeing informatics
- Worldwide medical services frameworks
- Worldwide wellbeing informatics
- Translational exploration informatics
- Home consideration
- Complex clinical choices
- Evidence-based medicine
- Disease management

Figure 7. Various conjunctions of medical informatics

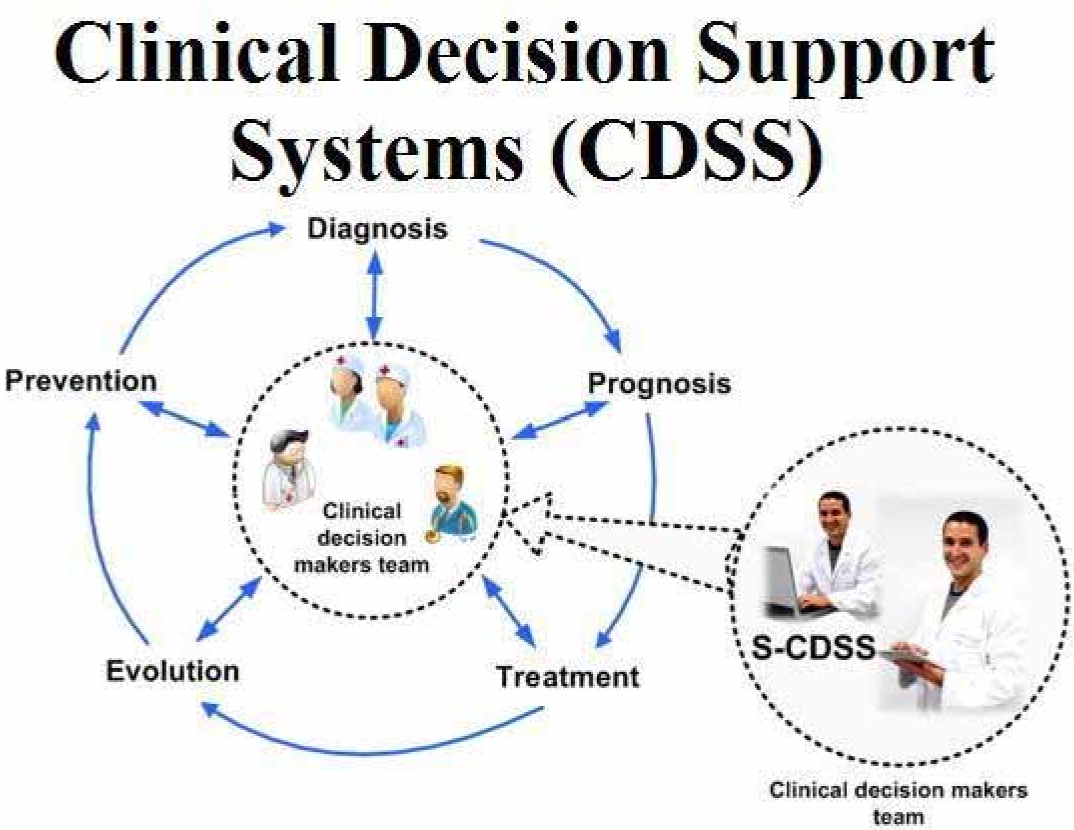


4.2. Clinical Decision Support Systems

A clinical decision support system (CDSS) is a software program that analyses data to assist medical professionals in making sound decisions and improving patient care (Jutai, Tuazon, et. al. 2021). It's a type of decision support system that's often used in corporate management. A CDSS focuses on leveraging knowledge management to provide clinical advice based on a variety of patient-related data elements (Stasolla, Matamala, et. al. 2021). Clinical decision support systems provide integrated processes, provide aid during care, and make recommendations for treatment plans. In the clinical setting, below are some examples of technology:

- Computerized Charting
- Computerized Medication
- Administration System
- Electronic Patient Monitor
- Mobile Medical Records

Figure 8. Demonstrating dimensions of CDSS [37]



4.3. Prosthetics and Pharmacy

Amputees now have more mobility than it has ever been because of computer assistive prosthetic devices. Prescription accuracy and patient safety are ensured by computers at the pharmacy (Rosner, Perlman, et. al. 2018). A prosthesis is a device that replaces a missing bodily part, such as one lost at birth, in an accident, or by amputation. Many amputees have lost a limb due to cancer, diabetes, or a serious infection.

A prosthesis could also be an option for reconstructive surgery, such as the removal of the breast after breast cancer.

Figure 9. Reconstructive surgery using prosthetics

4.4. Administrative Applications

The global computerized management systems have been found to computerize a wide variety of health-care technology organizational processes. The unifying aspects of these app development environments include modular design and division-oriented structures (Rosner, Perlman, et. al. 2018). In today's world, there is a lot of automation of administrative applications. As an example:

- Scheduling appointments in a doctor's office
- Computerized billing used by an insurance
- clerk or accounting department

4.5. Computer-Assisted Surgery

Robotic surgery is another name for computer-assisted surgery. As technology advances, this use is becoming increasingly popular (Rosner, Perlman, et. al. 2018). It is showing to be advantageous in several ways:

- The robotic hand is steadier and more precise than a human hand
- Reducing the amount of time a patient must stay under general anesthesia
- Smaller incisions required
- Decreasing the amount of time a patient stays in the hospital

Figure 10. Computer assistive robotic surgery

4.6. Computer-Assisted Devices

The major goal of assistive devices and technologies is to preserve and enhance patients' functionality and free them from dependency to improve their living conditions & comfort (Rosner, Perlman, et. al. 2018). The following are a few examples of assistive devices:

- Enhance and help people to hear who are suffering from hearing-related issues and disabilities.
- People suffering from memory issues, attention seekers for care, or any other challenge related to brain skills are assisted with computing electrical assistive devices known as Cognitive aids.
- Voice recognition apps, screen displays, and screen magnification applications are examples of information technology tools that assist persons with mobility and sensory limitations in using computers and mobile devices (Rosner, Perlman, et. al. 2018).
- Precise physical changes in the architectural designs such as ramps, grab rails, and doorways to enable easy accessibility to buildings, workplaces, and public spaces.
- Launching various devices with functionalities to assist in daily chores such as cooking, grooming, and tech aids to extend their reach are a few examples (Rosner, Perlman, et. al. 2018).

Figure 11. Computer assistive hearing device

5. DEVICES

The computer assistive devices used for monitoring and tracking patient healthcare and engagement can be classified broadly in the following categories:

5.1. Mobility

Computer-assisted mobility devices are being utilized to help people walk or move to preserve and improve a patient's functionality and independence, as well as their general well-being. Patients with chronic conditions or amputees now have greater mobility than ever before (Lontis, Lund, et. al. 2010). The following are a few examples of computer-assisted mobility devices that have been effectively used in healthcare:

- Wheelchairs
- Walking frames
- Mobility assisting sticks
- Tri wheel cycles
- Prosthetics
- Clubfoot brace

5.2. Vision Aids

Graphical interfaces for the sightless or screen optical viewfinders for low-vision computer users, multimedia magnifiers, other reduced vision reading and writing aids, and so on, are examples of devices that assist persons with vision impairment or other vision-related disorders (Lontis, Lund, et. al. 2010). A few examples of computer-assisted vision devices are as follows:

- Communication cards
- GPS applications for walking poles
- Eyeglasses & magnifying software

5.3. Hearing

People who are deaf or disabled by hearing capability use computer-assisted hearing devices, also known as assistive listening devices (ALDs), to help them communicate (Lontis, Lund, et. al. 2010). This technology allows the user to hear better in ordinary scenarios by overcoming the negative effects of background noise and distance. ALDs can be used in conjunction with a cochlear implant to improve a person's ability to hear specific sounds.

- Hearing aids
- Hearing loops

5.4. Communication

The doctor can use assistive communication systems or technologies to keep track of the patient history, diagnostic report, & health status. In addition, the doctor can engage with patients, recommend medical examinations, and write prescriptions (Cincotti, Aloise, et. al. 2007). Doctors can easily deliver treatment and care to patients located anywhere in the world using an effective communication device. Here are a few examples:

- Eye movements based on Communication boards
- Picture based instructors

6. IMPLICATION OF COMPUTER ASSISTIVE TECHNOLOGY DURING COVID PANDEMIC

Individuals' engagement in regular chores such as mobility, attending school, visiting the workplace, and access to health management systems has been disrupted by COVID-19 disease (Cincotti, Aloise, et. al. 2007). While these events have happened around the world, the COVID-19 epidemic has added vulnerability and marginalization to lives with functional impairments, such as persons with disabilities, chronic illnesses, or disabilities due to aging.

Even in non-pandemic times, evidence reveals that patients with disabilities have worse socioeconomic positions, low employment ratios, poorer general health, & greater poverty rates (Cincotti, Aloise, et.

al. 2007). Most of these variables sum to the designation of these persons as miserable people in the context of a pandemic, which may lead to further exclusion from the community in the name of sickness.

Understanding the underlying issue is necessary for promoting access to medical framework, health care, and involvement for people with disabilities, chronic disease, or disability due to aging who rely on assistive technologies. During COVID-19, there was a major disruption in services for obtaining computer assistive technology, with numerous main causes (Pradhan, Bhattacharyy, et. al. 2021). The problem most frequently noted was a lack of availability of facility providers and one on one support.

Provider's issues of availability were linked to a variety of circumstances, including provider illness, the shutdown of transportation and delivery due to lockdown guidelines, and the redeployment to other areas of medical requirements. In certain zones, the service cuts resulted in "overwhelmed providers, exacerbated by staff reductions during the quarantine period"(Pradhan, Bhattacharyy, et. al. 2021). As a result, providers said they had difficulty providing suitable services "while keeping adequate social distance." Because in turn to provide service, before that we need to know the patient, perform the evaluation, take measures, test, and adapt without having direct interaction with them."

As a result of the pandemic, Assistive Technology users have identified the lack of one-to-one support as a significant barrier. Individuals' capacity to avail and access the technology, including developing a crucial skillset for independent usage, was hampered by their inability to receive dedicated support (Pradhan, Bhattacharyy, et. al. 2021). "Even with the AT, some deaf and blind people still rely on a communication partner to help them use the devices to communicate," according to the report. Furthermore, "for people who require the assistance of a support worker to aid with the use of AT, there may be a problem in obtaining appropriate support and training support employees to assist the user (Pradhan, Bhattacharyy, et. al. 2021)."

To overcome the situation, the usage and availability of special and personalized devices are designed and manufactured, or checked for normally available; whose basic purpose is to enhance or improve a patient's functioning and independence, should be promoted for their well-being.

7. CHALLENGES

Humans can use assistive technology to live healthy, independent, useful, and gracious lives, and also to contribute to education, healthcare as well as personal welfare. The demand for formal fitness and guidance services, long-term care, and painting careers is reduced by assistive technology. Humans are often facing the issues related to less income and being imprisoned in poverty in the absence of assistive edge technology, worsening the impact of illness and causing disability on a person, their family, and even society.

Some of the Open Challenges associated with Assistive Techniques are:

1. Regional Obstacles:
    a. There aren't any national policies or programs in place.
    b. Inability to accurately assess user needs and provide services to various groups.
    c. Aging, disability, non-communicable diseases, and non-fatal injuries are all proxy measures of regional market size.
    d. Emergency scenario in the event of a calamity such as an earthquake, tsunami, or another natural disaster.

2. Educational Obstacles:
   a. Inadequate rehabilitation services, including a lack of qualified personnel and inadequate assistive product quality
   b. People's lack of knowledge and awareness.
   c. Expertise, which comprises skilled knowledge, is lacking.
3. Socio-Economic Barrier:
   a. A big challenge in AT is a lack of finance.
   b. Scarcity of resources.
4. Standardization issue:

A significant number of suppliers produce a diverse range of items in the healthcare industry. In the design process, the majority of these items claim to follow conventional norms and protocols. However, there is a lack of validity. As a result, the formation of a dedicated organization that can standardize the IoT sensors, which will be based on communication protocols, data accumulation, data storage, and gateway interfaces.

8. CONCLUSION

Those people who can receive upper-extremity prostheses (UEPs), in which rejection rates are high, owing to pain with the devices, their limited capacity to satisfy individual demands, also lack training in their use, and their limited permanence is the major issue behind it. Some of the following conclusions can be drawn as a result of these factors:

- When suitable products and technologies are available, they are properly prescribed and fitted, the user receives proper training in their use and appropriate follow-up, and societal and environmental barriers are restricted. Assistive products and technologies hold promise for partially or completely mitigating the effects of impairments and enhancing work contribution.
- It's critical to comprehend the complexity of aspects that must be optimized to improve function when connecting people with appropriate assistive items and technologies. Selecting, creating, or customizing the proper equipment for an individual, as well as providing training in its use and adequate record, are all difficult but crucial steps in maximizing tasks among users of assistive devices and technology.
- Access to coverage for assistive items and technologies, as well as related services, may be influenced by socioeconomic class and educational levels. A multitude of characteristics, including educational level, are linked to health literacy. People's understanding of their needs, device and treatment alternatives and resources to pursue the devices they require may all help them get assistive devices. Furthermore, for the youth of transitional age, a loss of access and coverage is a substantial hindrance to their independence, transfer to employment, occupational preparedness, or further education.
- Access to suitable assistive products and technologies, as well as qualified providers and teams with the knowledge, skill, and expertise required to properly evaluate, fit, train, and observe people using those products and technologies, is often limited and varies from each other.

- Professionals making disability decisions cannot infer that just because a person uses an assistive product or technology, the item is constantly helpful for a person, which reduces the impact of impairment, or it allows the person to work easily. Environmental, societal, and individual issues must all be considered.
- More research is needed to know how the specifications for and use of assistive technologies, products, and associated services affect disabled people's involvement in society and work participation. Such study could help to improve not only awareness in these fields, but also the establishment of reasonable resource usage, such as cost-benefit evaluations and exposure for devices and related services can be identified.

9. FUTURE SCOPE

More study and assessment can be done to better understand the primary motivations and barriers to using assistive technologies as an adjunct to existing care models for the best management of health care needs, particularly in the elderly and those with chronic medical problems. Assistive technologies can benefit not only patients and caregivers but also healthcare services. Local services are constantly in demand, which is exacerbated in times of crisis, such as the present COVID-19 outbreak. In this situation, the service provided by the assistive device may be useful in ensuring the long-term viability of health and social care by encouraging shared care. Assistive technology's definition and scope may need to be updated as traditional assistive technology collides with other fields such as medical technology and neuroscience.

Humans may be able to achieve feats that they would otherwise be physically or cognitively incapable of achieving without the use of technology thanks to body-integrated solutions. The distinction between assistance and extension or enrichment, on the one hand, may become more definite in the future, or these terms may instead meet into seamlessly incorporated solutions that offer enhanced sensory sensitivity for people with or without impairments – dubbed "assistive augmentation" recently.

End-users will test, approve, and accept certain emerging items, and some technologies will become mainstream rather than a specialist. The user behaviors and tastes may also change. This will likely lead to the replacement of certain traditional products with emerging assistive products; conversely, socioeconomic factors, user preferences, demands, and demography may lead to a continuation of the current scenario.

Although assistive technology is designed to improve people with disabilities' engagement in society, some assistive technologies may have the contrary impact. Emerging technologies like companion robots, smart homes, and wearable help people live independently, but there's a risk that they'll encourage people to believe that a person's caregivers can be replaced by machinery, leading to even more social isolation for end-users. Some cultures may be more concerned about this than others. There will be a need to ensure that human care is still regarded as essential. Age, cultural relationships, and the perceived ease of adopting new technology, as well as the availability of emerging solutions for end-users in developing nations, all raise similar worries about the societal divide. These issues underscore the need for educating and making a diverse selection of items available to meet a variety of requirements and preferences.

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Chapter 6
A Machine Learning Approach Towards Heart Attack Prediction

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ABSTRACT

Various types of heart diseases and conditions leading to increasing chance of heart attack have been a serious concern all over the world. Several factors like blood pressure, cholesterol, diabetes, obesity can affect the heart, and thus, those should be monitored regularly to prevent the chance of heart attack in people of different age groups. This chapter at first has analyzed different existing benchmarks of heart attack analysis. Being motivated by the shortcomings of the state-of-the-art literature and to address the challenges, it has introduced support vector machine, the most popular supervised machine learning algorithm to classify the chance of heart attack using a dataset downloaded from Kaggle. The experimental result has been evaluated using different performance metrics, including accuracy, error rate, precision, recall, F1 score. Finally, the performance has been compared with the existing related works also to validate its effectiveness and efficiency in real-time heart attack prediction.

INTRODUCTION

According to World Health Organization, 12 million deaths happen to cardiovascular disorders every year. In most countries, due to heart diseases, the maximum of deaths happen. When a coronary artery becomes unexpectedly clogged, blood cannot circulate to all parts of the heart muscle. As a result, a fragment of heart muscle can't obtain adequate oxygen; in that situation, a heart attack occurs. Life relies on the element that operates the heart since the heart is a vital part of our body. Coronary illness

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is an infection that influences the heart's activity (Marimuthu et al. 2018). It has numerous names like cardiovascular sickness and blood vessel hypertension (Alotaibi 2019). The obstacle is normally caused when a plaque cracks. If the bloodstream isn't re-established hastily, also by a medication that breaks up the obstacle or a catheter located inside the channel that essentially opens the obstruction, the piece of the heart muscle will die.

As per the Indian Heart Affiliation, half of all cardiovascular failures in Indians happen under 50 years of age, and 25% of all cardiovascular failures in Indians happen under 40 years of age. In India, additional 17 Lakhs individuals pass away consistently because of heart illnesses. In Asian nations also, 22% of the transient (in all-out coronary illness passing) are because by Cardio Vascular Disease (CVD) (Lakshmanarao et al., 2019). Clinical experts working on coronary disease have their limits; they can forecast the probability of respiratory failure with up to 67% precision (Sharma, H. and Rizvi, M.A., 2021). In the current pandemic situation also, specialists need a backing network for a more exact prognosis of coronary illness so that proper rehabilitative aid (Ghosh, Saha, and Konar 2020) (Saha and Ghosh 2019) can be prescribed in proper time by consultation with a doctor. Respiratory failure can have various indications, some of which are extra normal than others. Normal respiratory failure indications are chest torment (angina), shortness of inhalation or trouble breathing, vomiting or stomach uneasiness, heart palpitations, nervousness, sweating, trembling, faint, etc.

The cause of Cardiovascular failure or heart failure is several for several people. The obstacle in blood veins happens due to different causes, such as harm to platelets, the body system, harm to heart muscles, and a lot more. The cause behind Cardiovascular failure is exercise less life, alcohol & smoking, age factor, diabetes facts, stressed lifestyle. Cardiovascular failure or heart failure is generally analyzed by a medical care supplier, which analyses a cardiovascular failure utilizing the set of experiences and symptoms, lab testing, heart-explicit symptomatic tests, imaging tests, etc. But the process is much more costly and takes a lot of time (Oxenham and Sharpe 2003). Thus, nowadays, doctors are adopting many scientific technologies which are very useful to predict diseases. However, sometimes doctors cannot decide whether the patient has undergone heart failure or not. So, in this scenario, machine learning systems can help the doctor make the right decision.

Thus, this chapter has attempted to save the existence of cardiac arrest patients and portraits a method for diagnosing the patients based on their clinical records. So, there is a huge scope of exploration in the prognosis of coronary illness in a person. In this chapter, we have designed a machine learning framework to predict the chance of heart attack. We have obtained data set from Kaggle with 303 instances and 13 attributes. Python has been used to build up the classifier. Compared to the other classifiers, Support Vector Machine (SVM) after hyperparameter tuning has shown the best performance for the given dataset, with 84% accuracy in testing and 87% accuracy in training. The proposed approach is well suited in its concerned domain since it has outperformed the existing benchmarks of state-of-the-art literature.

The rest of the chapter is organized as follows. The next section discusses and analyzes some existing frameworks of heart attack prediction using machine learning. Section 3 explains the working mechanism of SVM used as the classifier in our proposed framework. Section 4 describes the experimental result and compares it with some related works to evaluate its effectiveness in the real-world scenario. Finally, section 5 concludes the work and discusses the possible future extensions for better efficiency.

LITERATURE SURVEY

Various researchers have targeted heart attack prediction as to their exploration point (Sharma and Parmar 2020) (Waqar et al. 2021). Sometimes sudden shocks also affect the heart condition, so mental health monitoring, early detection of stress (Sagayam et al. 2021), anxiety, and depression are also required (Chanda et al. 2022). Santhi *et al*. (Santhi et al. 2021) planned a framework appropriate for continuous coronary illness prognosis, and it can be utilized by clients who have heart disease. The diagnosis arrangement of the framework can forecast coronary illness by utilizing the Machine Learning (ML) method, and the forecast results depend on the occasion of the coronary illness dataset. To raise the caution by looking at the changes, they have assumed that the client's pulse increases more than the normal pace of the heart. To demonstrate the adequacy of the framework, tests have been done for both observing and analysis frameworks. Swathy *et al*. (Swathy and Saruladha 2021) provide us comparisons and reports of numerous classification, Machine Learning, Data Mining, and Deep Learning representations utilized for the prognosis of heart illnesses. The review is prepared as 3-fold: classification and data mining methods used to diagnose heart diseases, ML system for heart diseases, and Deep Learning Replicas for heart disease prognosis. The presentation metrics utilized for broadcasting the precision, the dataset utilized for prognosis and classification, also the tools utilized for each class of these methods are also run and stated in this study.

Marimuthu *et al*. (Marimuthu et al. 2018) explain the current method and provide a general outline of the present work. The techniques they talk about are Artificial Neural Network (ANN), Decision tree, Fuzzy Logic, k-Nearest Neighbor (kNN), Naïve Bayes, and SVM. By utilizing various forms of data mining and ML methods to analyze the event of coronary illness have summed. There are a few treatment strategies for patients if they are determined to have the exact type of coronary illness. There is a requirement for combinational and additional perplexing models to raise the precision of the prognosis at the starting stage of coronary illness. The method will be very knowledgeable with the additional features being taken into the data set. Numerous probable improvements could be analyzed to improve this prognosis method's scalability and precision. Singh *et al.* (Singh and Samagh 2020) present an orderly survey of various kinds of ML strategies to prognosis heart sicknesses. The investigation of different exploration works done regarding the use of ML in the prognosis of heart sicknesses based on datasets is introduced there. Present exploration work will help the clinical professional's prognosis the heart intimidation well on schedule to go to the measure to control the accident. An insightful review has been directed for the current procedures and thought about discovering the effective and precise method. These faction and inventive models might work on the presentation of heart sicknesses prognosis, with the assistance of which early identification of heart illnesses in patients can be made. These methodologies might help the clinical specialists prohibit the incidents by giving prophylactic treatment.

Sharma *et al.* (Sharma, H. and Rizvi, M. A., 2021) have summed up state-of-the-art methods and obtainable strategies for the prognosis of this disorder. Deep learning, an emerging space of AI, showed a few promising outcomes in another area of the clinical determine to have high exactness. A few deep learning strategies have been discussed executed for coronary illness prognosis alongside pioneer ML. An analytic examination has been accomplished to discover the best available algorithm for the clinical dataset. Table 1 compares existing benchmarks of heart attack prediction using ML. Deep learning has also proved its efficiency in recent works aiming toward heart attack prediction (Ashraf, Rizvi, and Sharma 2019) and heart health monitoring (Ali et al. 2020).

Table 1. Comparison among related literature

Ref.	Contribution	Techniques Used	Performance	Limitation	Proposed model's way of overcoming the limitation
(Manikandan 2018)	The execution of this model uses the dataset acquired from UCI's ML repository, Rapid Miner, to purify the dataset and Anaconda v2.7 packages to develop the classifier. The forecast outcomes are made accessible to the purchaser with the assistance of a web interface exceptional with a simple to-utilize realistic UI. Rapid Miner was utilized to build up the best fitting algorithm for the given dataset, and four algorithms are used Naïve Bayes, KNN, Decision Trees, and Random Forest. Also, Random Forest was analyzed by building their processes in Rapid Miner. Among all the algorithms applied to the dataset. A similar classifier can be gotten to with a web interface for the client's accommodation.	Four algorithms Naïve Bayes, KNN, Decision Trees, Random Forest.	Naïve Bayes has given the best precision of 81.25% among all algorithms.	Classification accuracy is not up to the mark. That's why their future plane is used recently introduced classification method to improve accuracy.	We used the SVM and got better accuracy because SVM is smarter than other classifiers. Moreover, SVM is well known for reducing error.
(Kumar et al. 2020)	They worked on the coronary illness dataset obtained from the UCI archive; it has ten features and a center with 304 cases. First, data is partitioned into 60% for training and 40% for the test; then, at that point, the dataset is uncovered to 5 ML classifiers like Decision Tree, SVM, Random Forest, KNN, Logistic Regression. Next, they determined the exactness of the classifiers utilizing a confusion matrix.	Five algorithms, i.e., Decision Tree, SVM, Random Forest, KNN, Logistic Regression	The random forest method has greater precision of 85.71%	They used only ten attributes. Consideration of more attributes could improve the accuracy.	All 13 attributes of the dataset have been used in the proposed model, which is vital for greater accuracy.
(Alotaibi 2019)	Their goal is to progress the HF prognosis precision utilizing UCI CVD dataset. Several ML methods were utilized to know the data and forecast the HF probabilities in a medical database. This study utilized five unique models to forecast coronary illness utilizing the gathered dataset. Therefore, this study deliberated, proposed, and executed an ML model by merging five different methods. In this study, they used a rapid miner device that calculated high precision.	Five methods, i.e., Decision Tree, Naïve Bayes, Random Forest, SVM, and Logistic Regression.	The Decision Tree classifier computed 93.19% accuracy highest accuracy among all classifiers	According to work, they use a small dataset size and partial no of patient's records; thus, the dataset was improved using proper techniques.	A data set obtained from Kaggle and the best attributes have been used in the present chapter.
(Patel et al. 2021)	Their experiment aims to calculate whether or not a patient will grow coronary illness. This experiment was done on managed ML arrangement procedures utilizing Decision tree, Naïve Bayes, Random Forest, and KNN in the UCI storehouse. Different analyses utilizing a unique classifier method were led through the WEKA tool. The information was pre-handled afterward. Finally, they were utilized in the model. KNN, Naïve Bayes, and random forest show the best outcomes in this experimental model. I tracked down the precision succeeding in carrying out four methods to be mainly elevated in KNN, and the value of k is 7.	Four data mining methods, i.e., KNN, Naive Bayes, decision tree, random forest	They found the highest 90.789% accuracy of using the KNN algorithm after implementing among four classifiers	Implementation of a more complex grouping of the system is needed to get more precision for the early prognosis of CVD. Different data mining techniques, like time-series clustering and association rules, SVM, and genetic method.	The SVM classification method has been used because SVM is smarter than other classifiers and it is well known for reducing the error

Continued on following page

Table 1. Continued

Ref.	Contribution	Techniques Used	Performance	Limitation	Proposed model's way of overcoming the limitation
(Nikhar, S., Karandikar 2016)	They proposed the coronary disease prognosis framework with various classifier methods to forecast coronary illness. The procedures are decision tree classifier and Naïve Bayes method; they have examined that the decision tree predicts better exactness as contrasted with the Naïve Bayes algorithm. Records with clinical traits were obtained from the Cleveland coronary Disease data set. With the support of the dataset, the sample important to the coronary failure analysis is extracted. The records were divided into two parts: the training and testing datasets. There are 303 records with 76 clinical attributes that were obtained. Be that as it may, they are dealing with a small number of characteristics, for example, just 19 attributes.	Decision tree and Naïve Bayes	Decision tree forecasts better accuracy	They hide their accuracy. I think their accuracy is not up to the mark	We have provided all the information about the work that has been done.
(Lakshmanarao, Swathi, and Sundareswar 2021)	The authors used ML strategies for coronary illness detection. They gathered a dataset collected from Kaggle for coronary illness prognosis. The dataset contains 4239 patients' records and 15 features. They want to forecast whether the patient has a long-term hazard of future coronary illness. The dataset contains 644 patterns of 10 Year coronary heart disease as one and the remaining pattern with 10 Year coronary heart disease as 0. As verdant datasets contain unequal prototypes of class format, they apply three testing procedures over the dataset. After applying testing methods, precision and review rates expanded definitely. For random oversampling, SVM provides the best precision. For Synthetic Minority Oversampling, Random Forest and Decision tree methods take for the best exactness. Finally, for Adaptive manufactured testing, Random Forest and Decision tree method provide the best precision.	SVM, Random Forest, Decision tree classifier	SVM gives the best accuracy of 99% for random oversampling among all other techniques. Random Forest and Decision tree for Synthetic Minority Oversampling give 91% accuracy. And also, Adaptive synthetic sampling gives 90% accuracy.	SVM did not give the best result for all the sampling techniques on their dataset.	In our work, SVM provides the best accuracy than other classifiers.
(Rajkumar and Reena 2010)	According to their work, the data alignment depends on the supervised ML method, allowing precision and time to create it. Tanagra equipment is utilized to describe the data, and the data is assessed utilizing 10-lap cross-validation, and the result is contrast. They Utilize the supervised ML method are KNN, Naive Bayes, and Decision list, and the outcome is contrast. Tanagra is a collection of ML; for data mining work. Therefore, the method can be applied straightforwardly to the dataset. This paper focuses on useful methods like KNN, Naive Bayes, and Decision list. The training data index formation of 3000 cases with 14 several features. As indicated by the exorcism, the dataset is partitioned into two sections which are 70% utilized for training data and 30% for testing.	Naive Bayes, KNN, decision list.	The naive Bayes algorithm did better performance giving 52.33% accuracy	Classification accuracy is not up to the mark. They use only three methods for classification. If they use SVM classifiers because SVM is smarter than others, I think they obtain more reliable accuracy of heart disease.	The SVM classification method has been used because SVM is smarter than other classifiers and it is well known for reducing the error

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Table 1. Continued

Ref.	Contribution	Techniques Used	Performance	Limitation	Proposed model's way of overcoming the limitation
(Srinivas, Raghavendra Rao, and Govardhan 2010)	They have introduced robotized and powerful coronary failure forecast strategies utilizing data mining procedures. Initially, they have given an expert obtainment for the extraction of the important model from the CVD data distribution centers for the well-organized prognosis of coronary artery Grounded on the intended important weightage, the common patterns taking value bigger than defined in advanced threshold were selected for the valued prognosis of the coronary artery. Three mining aims are distinctly grounded on data examination. All these replicas could reply to complex questions in a prognosis heart attack.	Decision Tree, Neural Network, Bayesian model, SVM for analysis of accuracy having a disease or without disease	The neural network model gives 89% accuracy for the disease class. On the other hand, the decision tree gives 89% accuracy for the without disease class.	Features like financial status, tension, pollution, and earlier therapeutic history were considered coal mining areas patients. Other data mining methods could also be used, like clustering, Time Series, Association Rules to explore patients.	In our work, SVM provides accuracy for the entire data set, not half of the patient.
(Prajwal et al. 2017)	Their goal is to progress a hybrid system that utilizes numerous machine learning methods similar to principal component analysis, Bag of Words replicas, and several classification methods. Utilizing this system, it is feasible to categorize an ECG sign as 1 of the 16 classes utilizing ML. Class 1 indicates normal ECG signs, classes 2 to 15 indicate numerous kinds of arrhythmia, and class 16 does not classify. The proposed technique utilizes the UCI ML Source dataset of heart arrhythmia to learn the model on 279 features. The utilization of ML helps in additional precision and high potential to predict extreme heart arrhythmia probability.	Four methods, Random Forest, SVM, Logistic Regression, and KNN classifier for classifying cardiac arrhythmia.	Support Vector Machine gave the best accuracy, which was 91.2%.	They include straightforwardly extricating features from an ECG signal. Apart from the 16 feasible classes that were taken in regard in this paper, the ECG sign can be characterized into several sets of cardiovascular arrhythmias.	In the future scope of this chapter, ECG datasets can be worked with for heart attack prediction.
(Rairikar et al. 2018)	They utilized 3 data mining method similar, Random Forest, Decision Tree, and Naïve Bayes, are addressed and utilized this method to progress a prognosis model which analyzes and forecast the chance of CVD. The primary goal of this important study work is to recognize the greatest classification method appropriate for giving the most extreme precision when classification for normal also abnormal somebody is carried out. In this way, the anticipation of survival deficiency at a prior stage is conceivable. The exploratory arrangement has been made to assess the performance of methods with the assistance of the CVD benchmark dataset obtained from the UCI ML store. The Random Forest method performs best and has 81% precision when similar to various CVD prognosis methods.	Random Forest, Decision Tree, and Naïve Bayes	Random Forest gives the best accuracy of 81% compared to other classifiers.	Classification Accuracy is not up to the mark. However, if they use SVM classifiers because SVM is smarter, it works faster than random forest. That's why their future plane uses a genetic algorithm in Decision Tree and Bayesian Classification; then, they can improve the accuracy.	The SVM classification method has been used because SVM is smarter than other classifiers and it is well known for reducing the error

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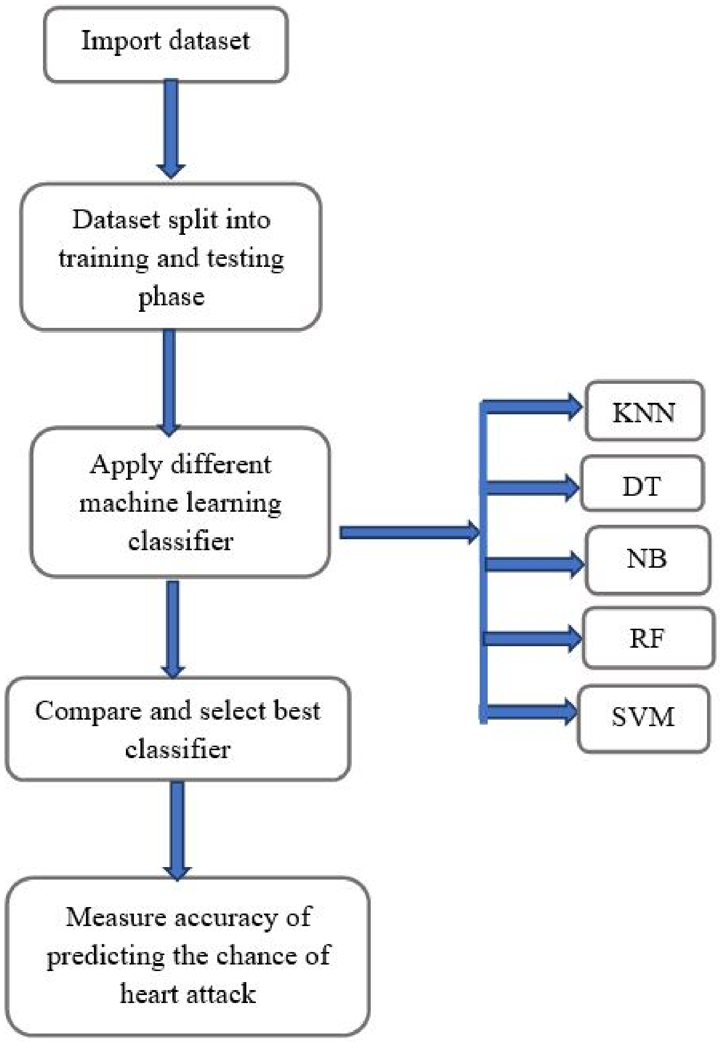
Table 1. Continued

Ref.	Contribution	Techniques Used	Performance	Limitation	Proposed model's way of overcoming the limitation
(Miao, Miao, and Miao 2016)	They used a high-level ensemble ML technology, and also an adaptive boosting algorithm was created for precise coronary illness findings and result prognosis. The created ensemble learning classification and a prognosis system were applied to 4 distinct data sets for coronary illness findings, including patients analyzed with coronary illness from the Hungarian Institute of Cardiology (HIC), Long Beach Medical Focus (LBMC), Cleveland Clinic Foundation (CCF), and Switzerland University Hospital (SUH). These 4 data sets have clinical instances of patients diagnosed with coronary illness: 303occurrences from the CCF, 294 cases from the HIC, 200occurrences from the LBMC, and 123 cases from the SUH. In every data set, each clinical case consists of 76 natural features. However, among the raw attributes, just 29 were utilized to forecast the development of the ensemble learning classification and forecast models. The testing results showed that the created ensemble learning classification and forecast models accomplished model exactness of 89.12% for HIC, 77.78% for LBMC,80.14% for CCF, and 96.72% for SUH, surpassing the exactness of already revealed research.	They used high-level ensemble ML technology and an adaptive Boosting algorithm	96.72% accuracy they have using Switzerland University Hospital data set.	They have errors between the model training and testing processes is an expected meeting known as an over-fitting issue in the field of ML during model progress. To overcome this problem, they can use the boosting algorithm.	We had no overfitting problems.

PROPOSED METHODOLOGY

Many types of research have confirmed that among the various kinds of machine learning classifiers, SVM provides more precision contrast to others. SVM is a Smart classifier it is well known for reducing the error. In the healthcare field, prognostic disease exploration is one of the useful and helpful applications of the Machine Learning prognostic method. Machine learning (ML) is thrust into classifying and prognosis data. In such conformity, numerous machine learning methods are utilized, according to the need of the dataset.

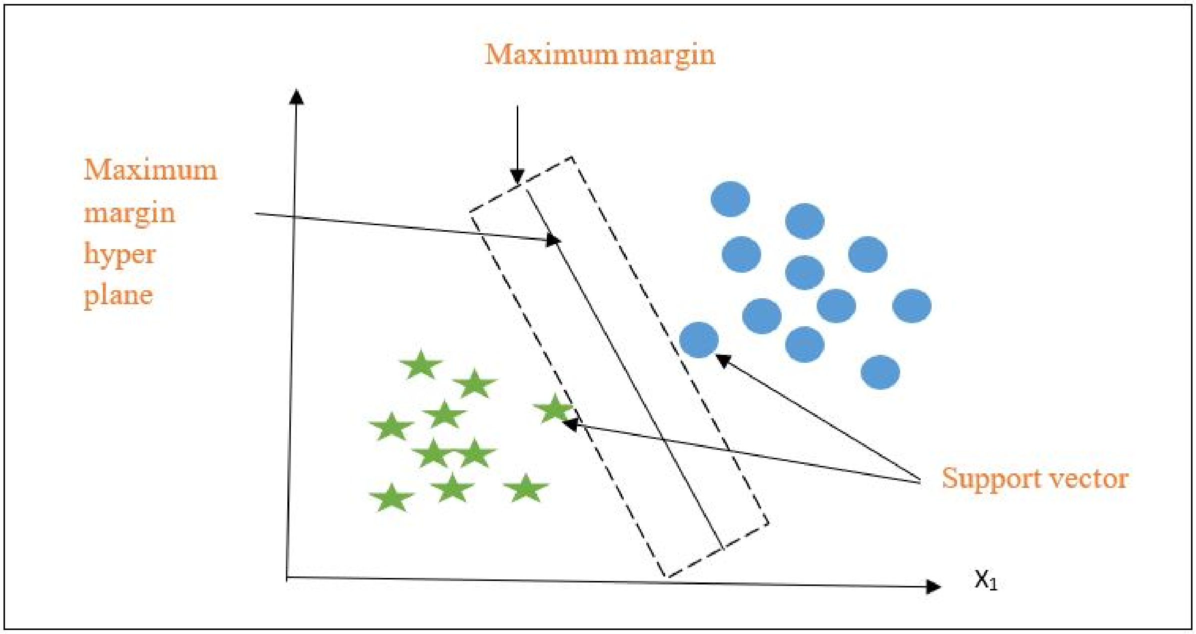
Figure 1. Overall block diagram of the proposed system



Support Vector Machine (SVM)

SVM is mainly famous as a Supervised Learning technique, which is utilized for classification and regression problems (Ghosh and Saha 2020). The objective of the SVM method is to build the best line or decision boundary between data points belonging to different classes, which is known as a hyperplane. It can cut off the n-layered gap into classes to place the new data element in the right class without any difficulty for some time. SVM picks the ultimate vectors/ point that assists in making the hyperplane. These ultimate cases are termed as support vectors, along consequent method named SVM. Using this hyperplane, Figure 2 classified data points from two different classes.

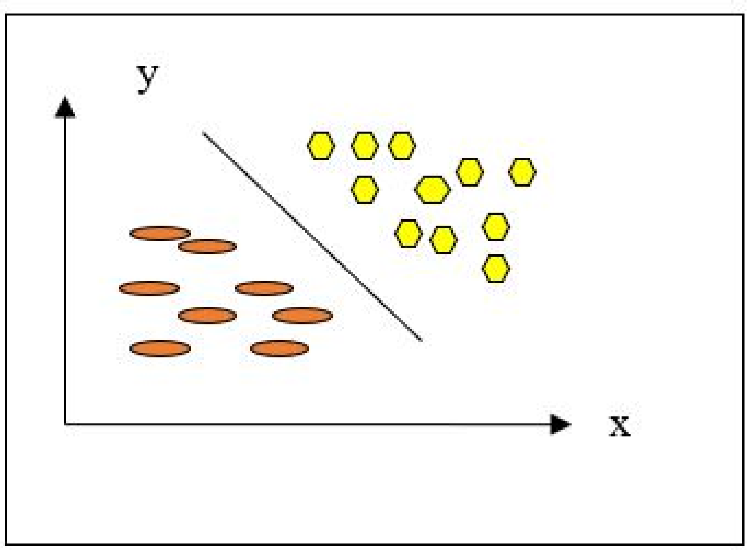
Figure 2. A pictorial illustration of SVM Hyperplane



There are two types of SVM, i.e., Linear SVM and non-linear SVM.

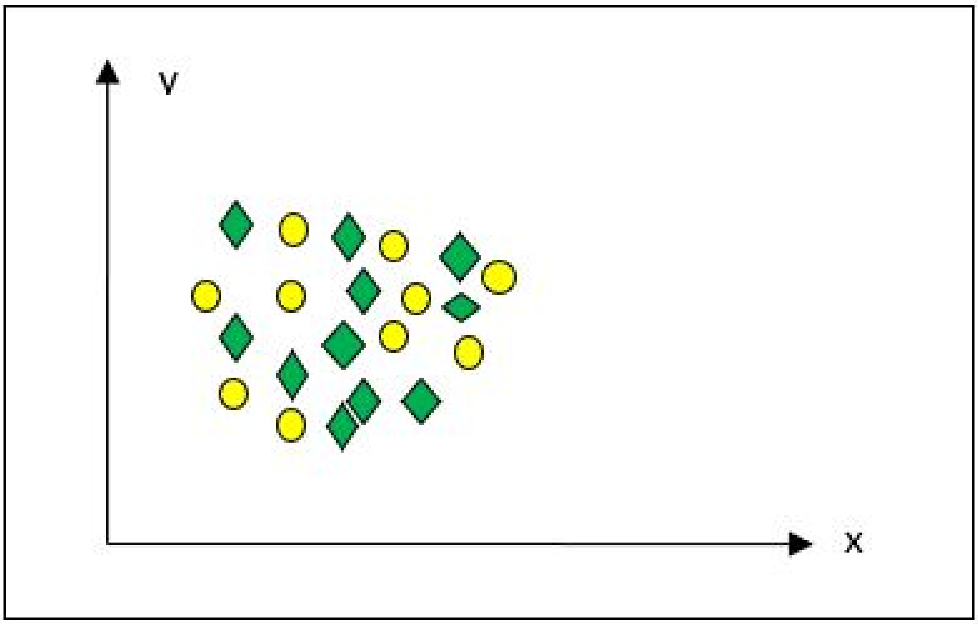
Linear SVM: This SVM is utilized when data are linearly separable. That means using a single straight line when the dataset can be categorized into two different classes. This kind of data is called linearly separable data, and in this case, the classifier is used as a Linear SVM classifier shown in Figure 3. The data points belonging to two classes have been represented with yellow and orange shapes, respectively.

Figure 3. Linearly separable



Non-linear SVM: This SVM is utilized when data are non-linearly separable. That means using a single straight line when the dataset cannot be categorized into two different classes. This kind of data is called non-linearly separable data, and in this case, the classifier is used as Non-Linear SVM classifiers shown in Figure 4.

Figure 4. Linearly not separable

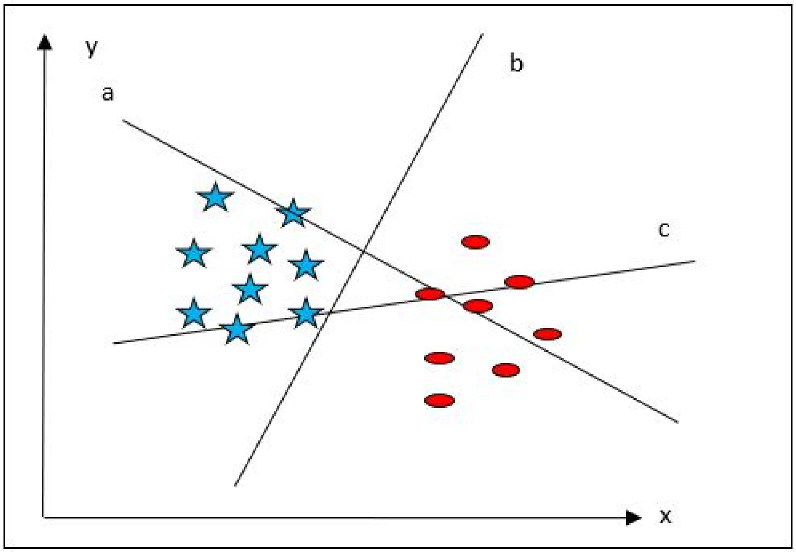


Working of SVM

The steps to follow in the classification process using SVM are mentioned below.

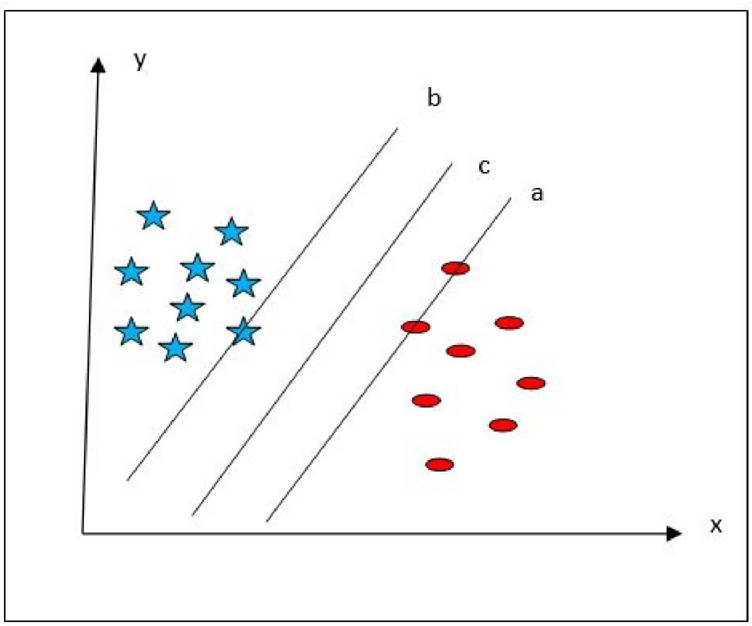
Scenario-1: In Figure 5, three hyperplanes (a, b, and c) have two input features, x, and y. Now the best hyperplane has to be picked for classifying circles and stars with the help of a thumb rule. In the above scenario, hyper-plane b should be chosen as the best because it accurately segregates both the classes circle and star compared to another hyper-plane.

Figure 5. Scenario-1



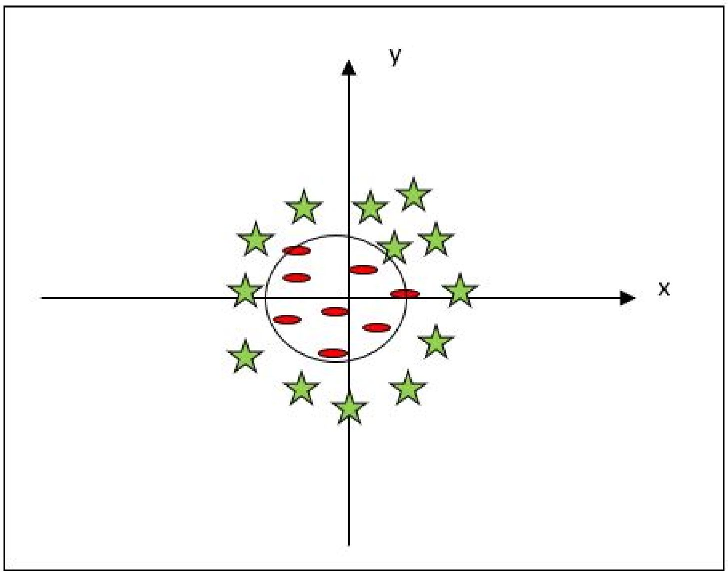
Scenario-2: In Figure 6, three hyper-planes (a, b, and c) have two input features, x, and y. Every hyperplane over there accurately separates the classes circle and star. But hyperplane c gets selected because the margin between the closest data point is in maximum contrast to the other hyperplanes. Miss classification can happen if a low-margin hyperplane gets selected.

Figure 6. Scenario-2



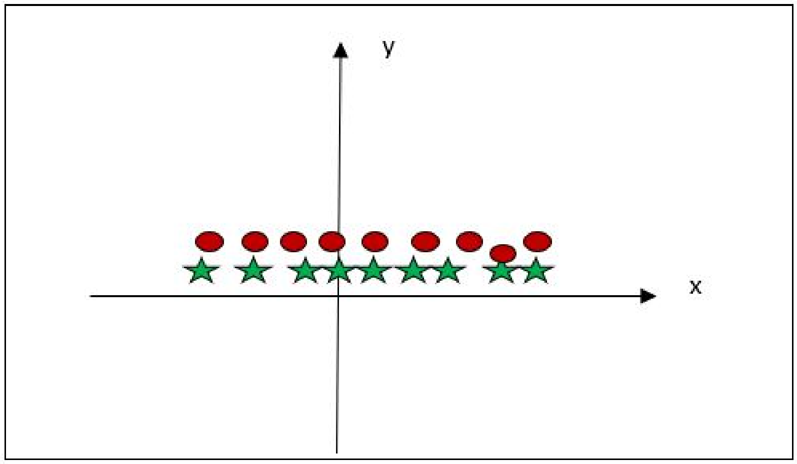
Scenario-3: Figure 7 shows a scenario where data are non-linearly separable, so a single straight line can't separate classes. SVM can solve this problem by adding a new dimension z using a kernel and calculating as $z=x^2+y^2$. Thus, z co-ordinate represents the square of the distance between the point and the origin. Now, after data plotting, it becomes linearly separable. Let the datapoint separating line in higher dimension get represented by z=k, where k denotes a constant. As $z=x^2+y^2$, $x^2 + y^2 = k$ is, representing a circle equation.

Figure 7. Scenario-3



The kernel used as a function transforms a small dimensional input gap into a higher-dimensional gap, translating non-separable problems into separable problems. It is used for most non-separable problems. So, we can get a plot of the data points like Figure 8.

Figure 8. Classification of separable data



Different Types of Parameters

There are some parameters to build the model of SVM (Duan, Keerthi, and Poo 2001). Some important parameters are "kernel," "c," and "gamma." These hyperparameters can be changed to improve accuracy. Selecting the correct kernel is crucial because the system can have very poor results if the transformation is not correct. As a rule of thumb, the linearity of data should always be checked, and linear SVM (linear kernel) should always be used. Linear SVM is a parametric model, but an RBF kernel SVM isn't, so the latter's difficulty raises with the size of the training set. Moreover, it is extra expensive to train an RBF kernel SVM. Still, you too have to keep the kernel matrix around, and the projection into this "infinite" higher dimensional space where the data becomes linearly separable is extra expensive throughout the prognosis.

Working of Kernel

The Kernel method takes data as input and transforms it into the required form of processing data. Various kernels like linear kernel, radial basis function kernel (RBF), polynomial kernel, sigmoid kernel, and others are there. RBF and polynomial kernel is required for non-linear hyper-plane. The kernel method returns the scalar product in exceedingly suitable feature space between two points. Thus, by defining a notion of resemblance, with a little computing cost even in the case of very high-dimensional spaces. The standard kernel function can be represented by

$$K(\overline{x}) = 1 \text{ when } \left\|\overline{x}\right\| =< 1$$

$$K(\overline{x}) = 0, \text{ otherwise} \tag{1}$$

Linear kernel: When we change the kernel to linear (kernel='linear'), we get output with linearly separable data. The linear kernel can be represented as

$$K(x,y) = sum(x \bullet y) \tag{2}$$

Gaussian kernel: It helps to separate the data points properly when not any previous knowledge about the data is there and can be denoted as

$$K\left(x,y\right) = e^{-\left(\frac{\|x-y\|^2}{2\sigma^2}\right)} \tag{3}$$

Gaussian kernel RBF: When we change the kernel to rbf (kernel='rbf''), it gets normally selected when non-linear data is concerned. It is a slightly improved version of the Gaussian kernel and can be represented as

$$K\left(x,y\right) = e^{-\left(\gamma\|x-y\|^2\right)} \tag{4}$$

Polynomial kernel: When we change the kernel type to poly (kernel='poly''), we get different outputs from the linear kernel. It is a further generalized depiction of the linear kernel. Due to less accuracy and efficiency, sometimes it gets less preferred than the other kernel functions. It is used in image processing and can be represented as

$$K(\mathrm{x,y}) = \tan \mathrm{h}\ (\gamma \mathrm{x} T^{y} + r)\mathrm{d} \text{ where } \gamma>0 \tag{5}$$

Sigmoid kernel: When we change the kernel type to linear (kernel='sig'), that acts as a substitute for neural networks and can be represented as

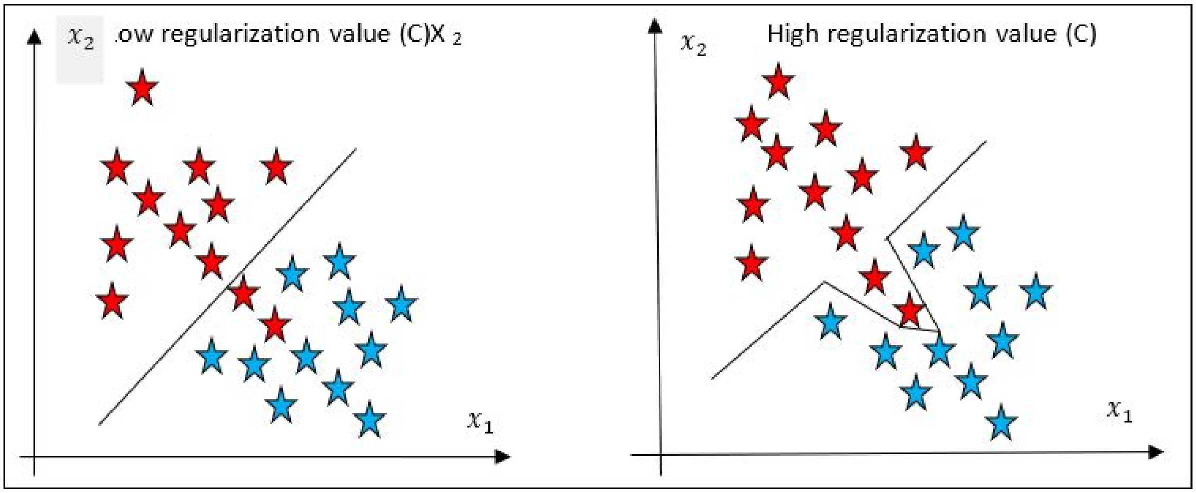
$$K(\mathrm{x,y}) = \tan \mathrm{h}\ (\gamma \mathrm{x} T^{y} + c) \tag{6}$$

This kernel function works very similarly to a two-layer perceptron model, which is an activation function of the neurons.

Working of C

Controlling error C is the regularization or penalty parameter in the SVM model and controls the decision boundary. The SVM optimization expresses how much miss classification for every training instance can be avoided. When c is low, a large margin for decision boundary is obtained. When c is high, a small margin for decision boundary is obtained. This is shown in Figure 9.

Figure 9. A pictorial illustration of the working mechanism of regularization as an SVM hyperparameter

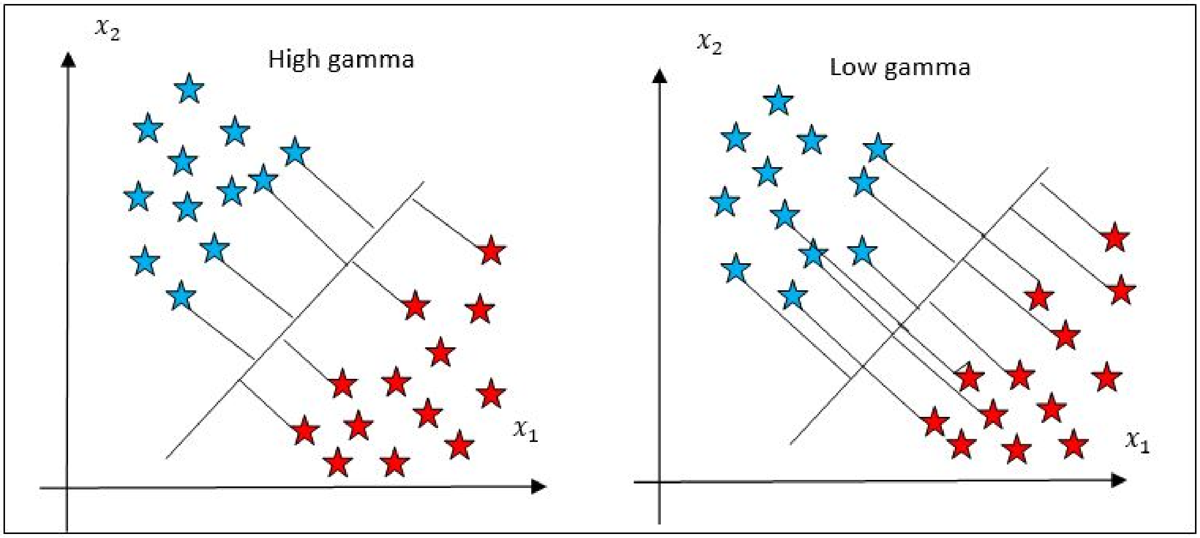


It is observed in Figure 8 the lesser value of C results in a higher margin. Eventually, many curves are not there, and the line is not rigidly following the data points even if two red data points were classified as blue. When the C is high, the boundary is full of curves, and all the training data was classified correctly. Although if all the training data points get properly classified, it doesn't imply that an increase in the C value always results in a precision increase due to the overfitting.

Working of Gamma

Gamma is a Kernel coefficient for polynomial, radial basis function, and sigmoid kernel. It specifies the extent to which a single training example has an impact. For example, this indicates that locations near the plausible hyperplane will be considered by high Gamma, while ones farther away will be considered by low Gamma.

Figure 10. A pictorial illustration of the working mechanism of Gamma as an SVM hyperparameter



As shown in Figure 10, the Gamma is reduced, determining the suitable hyperplane will evaluate points at longer distances, resulting in the utilization of more and more points (the black lines specify the points considered in searching for the best hyperplane). The gamma value ranges between 0 and 1. The value of Gamma must be explicitly entered into the code. The most favored gamma value is 0.1.

Working of Degree

The degree parameter gets applied only when the selected kernel is polynomial and decides the degree of the polynomial.

Working of Probability

In the case of the Boolean parameter, called probability, if true, the model will return the vector of probabilities belonging to every class of the target variable for each prediction. Thus, in a nutshell, it provides the level of confidence for every forecast.

Working of Shrinking

The shrinking parameter indicates if employing a shrinkage heuristic in our SVM optimization is a target utilized in Sequential Minimal Optimization. It's default setting is true. Unless you have a solid reason, don't alter it to false because downsizing will considerably increase your performance while sacrificing very little accuracy in most circumstances.

Mathematics Behind Hyper Plane

In Figure 2, we saw data are separable by a straight line, and the straight-line equation is

$$y = mx + b \tag{7}$$

Let, m= -1 where m is a slope, and b is a distance of origin to the line find a best separable plane equation is

$$y = w^T x + b \tag{8}$$

after applying dot product $w^T x$ (where w denotes a weight vector and x is a matrix input) we get two equations

$$w^T x_1 + b = +1 \tag{9}$$

for positive margin line and

$$w^T x_2 + b = -1 \tag{10}$$

for negative margin line
Equations 3 and 4 substitutes find the distance between two margin equations is

$$W^T (x_1 - x_2) = 2 \tag{11}$$

for optimization, the equation is

$$\frac{w^T}{\|W\|}\left(x_1 - x_2\right) = \frac{2}{\|W\|} \tag{12}$$

To make a correct prediction; we need to maximize the equation

$$\text{Max}\,\frac{2}{\|W\|}\ \text{such that}\ \ yi = \begin{cases} +1 & \text{if } wT \cdot x + b \geqslant 0 \\ -1 & \text{if } wT \cdot x + b \leqslant 0 \end{cases} \tag{13}$$

The point upstairs or above the hyperplane, which is defined as class +1, and the point under the hyperplane, which is defined as class -1

EXPERIMENTAL RESULT

This section explains the dataset preparation and performance of our proposed heart attack prediction system using Support Vector Machine compared to four more classifiers applied to the same dataset. The section concludes by comparing state-of-the-art literature and the statistical significance of our proposed SVM by two-tailed t-test.

Dataset Explanation

The dataset considered in the proposed heart attack prediction framework has been downloaded from Kaggle (Kaggle Dataset). It has thirteen features, namely patient's age, sex, exercise-induced angina, significant vessels amount, type of chest pain, resting blood pressure, cholesterol in mg/dl collected by BMI sensor, blood sugar in fasting, resting electrocardiographic results, angina due to exercise pattern, the numeric intensity of depression, sloping of the highest workout, and the extreme heart rate attained. Based on these features, the patient has been classified as having a more or less chance of heart attack. Furthermore, the training and testing ratio has been considered as 3:1, and a total 303 number of patients records have been analyzed using this.

Classification using Support Vector Machine

For two reasons, we choose SVM over alternative methods for categorization. To begin with, it has a good generalization and accuracy capability with a short training sample (Lesser, Mücke, and Gansterer 2011). It's the most reliable classification method for real-world settings, and it's been used to solve different types of problems, including facial recognition, handwriting character identification, and intrusion detection. It is created as a binary classification algorithm, but it has been improvised for multiclass problems. As it is not feasible to present confusion matrices for all the combinations of hyperparameters thus, only the matrices generated from the best combinations of hyperparameters like C and Gamma for the four kernels have been shown in Figure 11. Below is a description of different classification performance metrics used in the chapter and their mathematical interpretations.

Accuracy: It describes how frequently the model forecasts the accurate output.

$$\text{Accuracy}=TP+TN/\ (TP+FP+TN+FN) \tag{15}$$

Misclassification rate: it describes how frequently the system gives incorrect predictions.

$$\text{Error Rate}=FP+FN/(TP+FP+TN+FN) \tag{16}$$

Precision: It describes the amounts of exact outputs provided by the model.

$$\text{Precision}=TP/(TP+FP) \tag{17}$$

Recall: It is described as the availability of entire positive classes, in what way our model forecasts correctly.

$$\text{Recall}=TP/(TP+FN) \tag{18}$$

F-measure: This F-score supports us to calculate the recall also precision together. The F-score remains high if the recall is equivalent to the precision.

$$\text{F-measure}=2*\text{recall}*\text{precision}/\text{recall} + \text{precision} \tag{19}$$

ROC Curve: ROC plot is utilized to display the classifier's performance. The graph is a trade-off between the True Positive Rate(TPR) on the Y-axis also the False Positive Rate(FPR) on the x-axis.

Performance Assessment

The classification performance of the proposed system has been assessed using accuracy, precision, recall, F1 score, and error metrics. The learning curves for all the four kernels of SVM with the best combination (Gamma=1 and C=1) have been presented in Figure 12. Figure 13 shows ROC curves, and AUC values obtained from the ROC curves are shown in Table 2. The parametric sensitivity analysis has been presented in Table 2, where two performance metrics have been calculated using

$$\text{True Positive Rate}\left(\text{TPR}\right) = \frac{True\ Positive}{Total\ positive} \tag{20}$$

$$\text{False Positive Rate}\left(\text{FPR}\right) = \frac{False\ Positive}{Total\ negative} \tag{21}$$

And Area Under the Curve (AUC) depicts the entire two-dimensional Area underneath the region of the convergence (ROC) curve. Finally, table 3 shows the metric values obtained during testing for two considered classes for a chance of heart attack 'more' and 'less,' where it is observed that the linear kernel is the most effective one for the proposed framework, and the best observation from each kernel has been marked with bold.

Figure 11. Confusion matrix generated from the best combinations of hyperparameters for four kernels

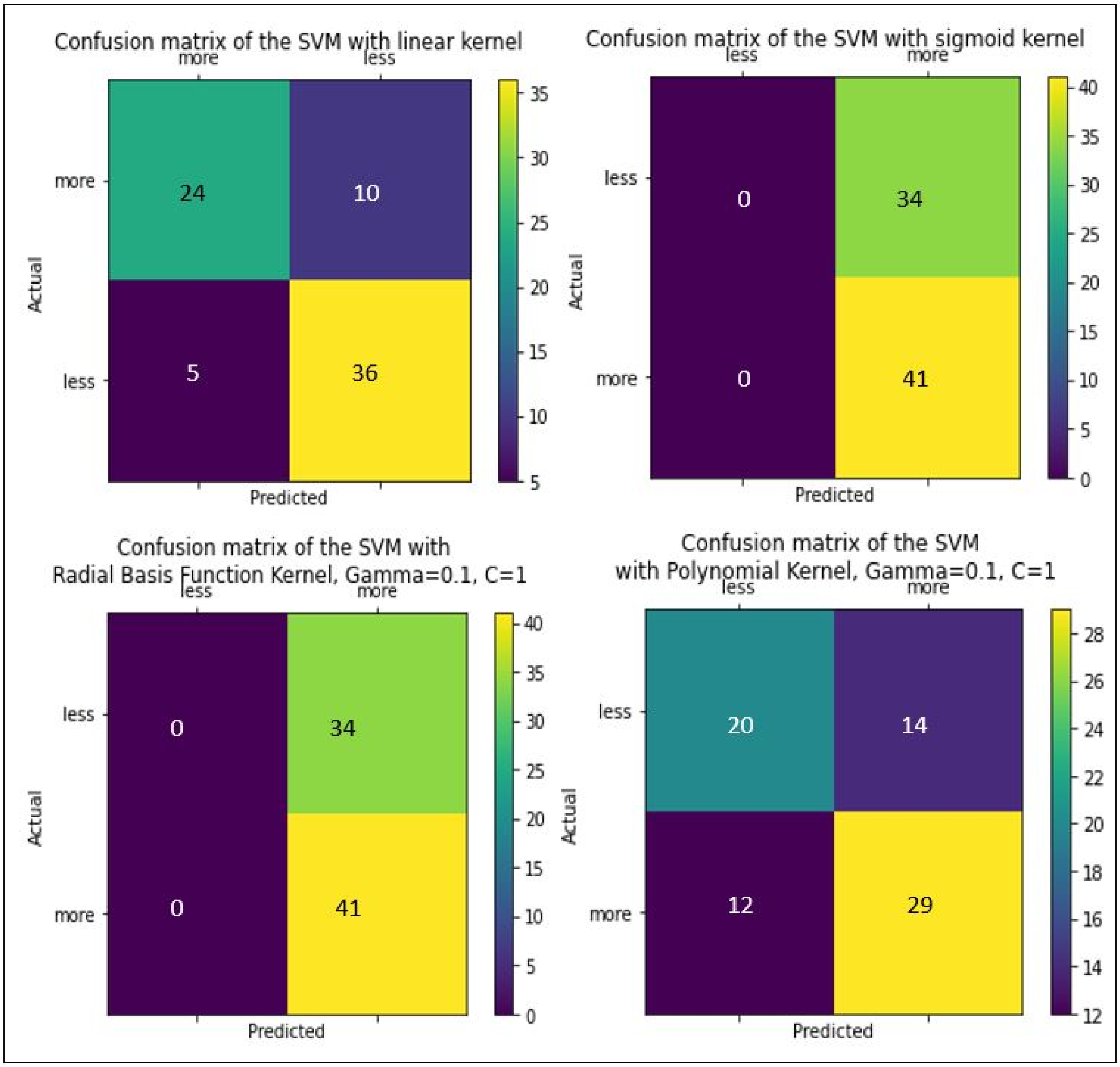


Figure 12. Learning Curves for the four kernels of SVM with the best combination (Gamma=1 & C=1)

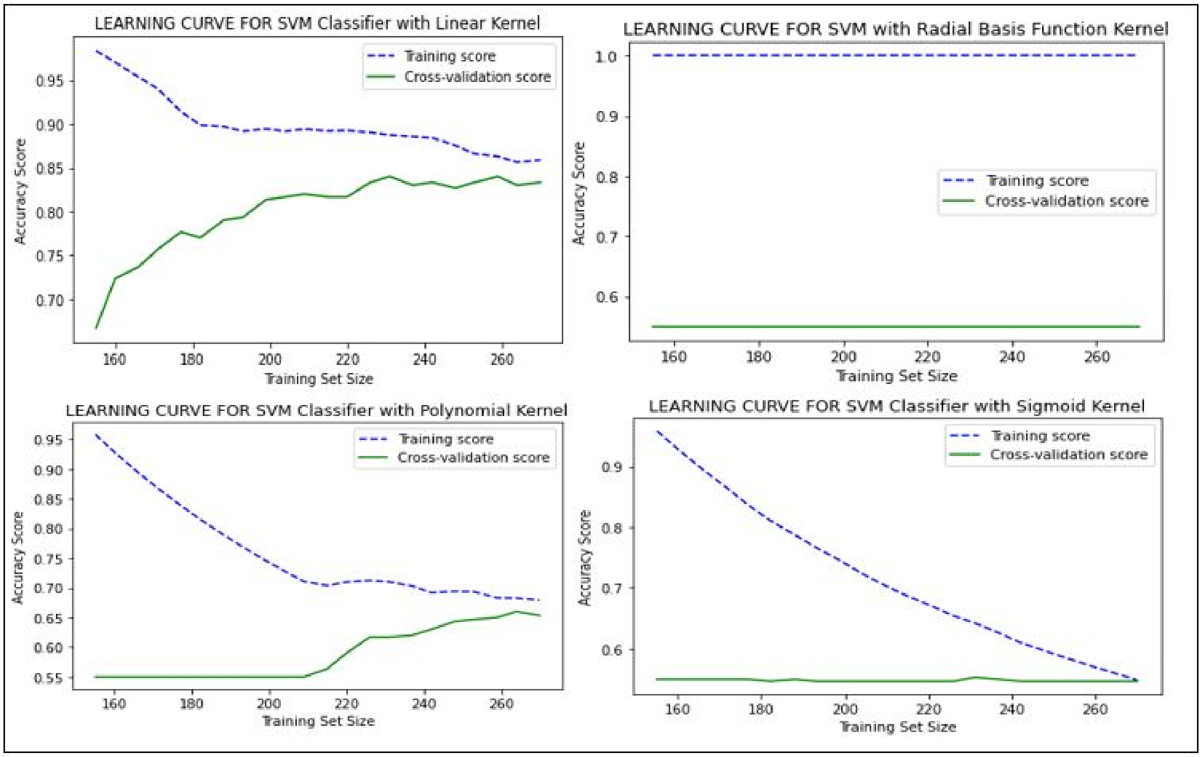


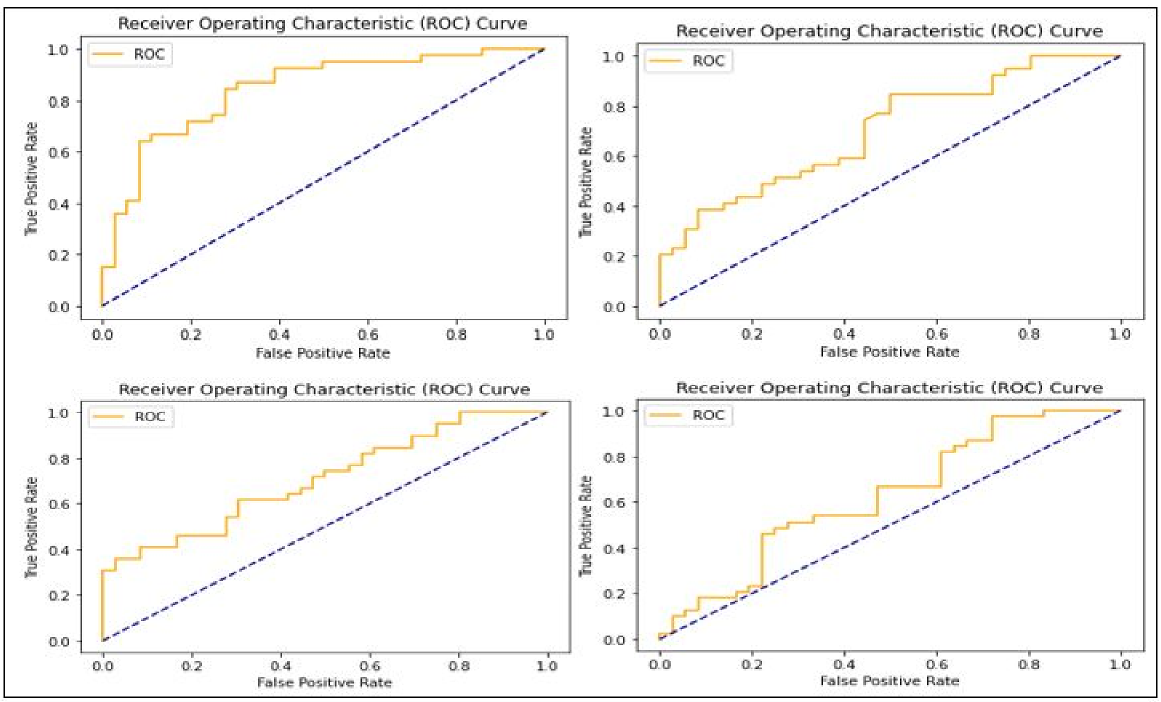
Table 2. Parametric sensitivity analysis of SVM as a classifier

Kernel value	Gamma value	C value	FPR	TPR	AUC
Linear	-	**1**	**0.12**	**0.71**	**0.831**
Sigmoid	-	**1**	**0**	**0**	**0.656**
Radial Basis Function	1	0.1	0	0	0.513
		1	0	0	0.513
		10	0	0	0.513
		100	0	0	0.513
		1000	0	0	0.513
	0.1	0.1	0	0	0.431
		1	0	0	0.431
		10	0	0.029	0.431
		100	0	0.029	0.430
		1000	0	0.029	0.569
Polynomial	0.1	0.1	0.292	0.588	0.701
		1	0.292	0.588	0.701
	0.001	0.1	0.15	0.706	0.793
		1	0.195	0.676	0.786
	0.0001	0.1	0.073	0.617	0.698
		1	0.073	0.617	0.785

Table 3. SVM based classification outcome in testing

Kernel	Chance of heart attack	Precision	Recall	F1 Score
Linear	More	0.83	0.71	0.74
	Less	0.78	0.88	0.83
Radial Basis Function	More	0.55	1	0.71
	Less	0.00	0.00	0.00
Polynomial	More	0.67	0.71	0.69
	Less	0.62	0.59	0.61
Sigmoid	More	0.55	1	0.71
	Less	0.00	0.00	0.00
Average				

Figure 13. Receiver Operating Characteristic Curves for the four kernels of SVM



Comparison Among Different Classifiers

For the comparative study, other classifiers, namely k Nearest Neighbor (kNN), Decision Tree (DT), Random Forest (RF), and Naïve Bayes (NB), have been compared with our proposed SVM in terms of accuracy, precision, recall, F1 score, and error. Table 4 depicts the mean and standard deviation values mentioned within the bracket for each performance metric by running five different algorithms 25 times. The means of each metric from the best and second-best algorithms have also been presented using the paired t-test. The statistical significance level of the difference of the means of the best two procedures has been presented in Table 4's last column, where '+' represents the t-value of 49 degrees of freedom is statistically significant at a 0.05 level of significance by two-tailed test, and the '–' represents that the difference of means is not statistically significant. The sample size for all of the t-tests is set as 25. The best one has been marked in bold.

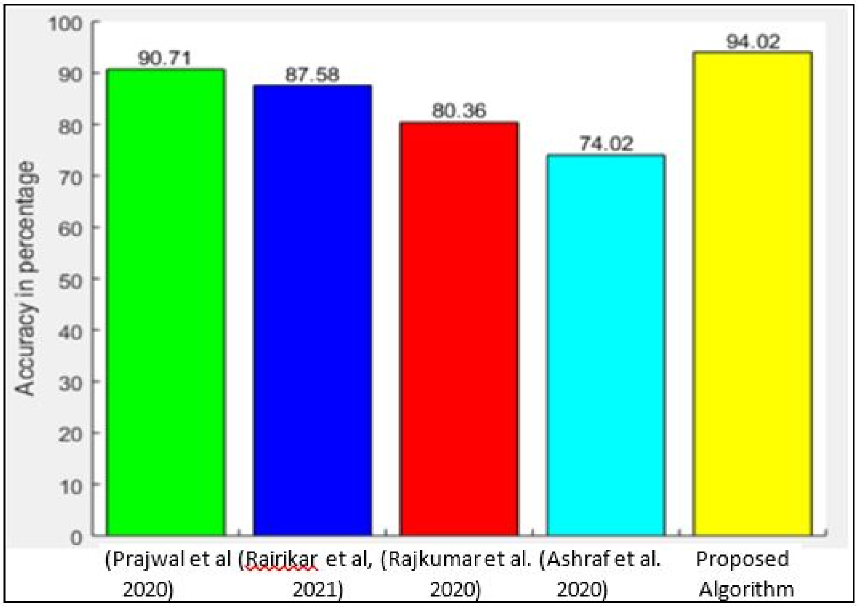
Table 4. Comparison of different heart attack prediction algorithms for 25 Runs

Performance metric	SVM	kNN	DT	RF	NB	Statistical significance
Accuracy	**0.83 (0.161)**	0.70 (0.531)	0.75 (0.657)	0.80 (0.645)	0.74 (0.314)	+
Precision	**0.89 (0.134)**	0.87 (0.634)	0.88 (0.453)	0.87 (0.564)	0.75 (0.324)	+
Recall	0.91 (0.168)	0.45 (0.324)	0.67 (0.498)	0.78 (0.654)	**0.93 (0.134)**	-
F1 score	**0.83 (0.015)**	0.74 (0.125)	0.67 (0.054)	0.78 (0.435)	0.74 (0.175)	+
Average error rate	**0.04 (0.016)**	0.40 (0.232)	0.25 (0.143)	0.65 (0.435)	0.19 (0.023)	+

Comparison with Existing Literature

Our SVM classification result has been compared by considering accuracy as the metric with the existing related works in Figure 14. The proposed approach's evaluation of effectiveness and applicability clearly shows that the proposed framework works better than the related ones.

Figure 14. Comparison with state-of-the-art literature



CONCLUSION

We have applied machine learning techniques for heart attack prediction in this chapter, which can be beneficial to prevent a heart attack if the chance gets detected at an early stage. We have collected a dataset from Kaggle with 303 instances and 13 attributes, and one target variable named output. When the output is 0, it indicates fewer chances of heart attack, and when the output is 1, it indicates more chances of a heart attack. Support Vector Machine has been used to classify the chance of heart attack based on different demographic features of the concerned subjects. It has provided better performance than other classifiers like K-Nearest Neighbor, Decision Tree, Random Forest, and Naïve Bayes. Hyperparameter running has also been done to achieve the best result by combining the best set of parameters for SVM. The time consumption will be attempted to be reduced and to improve the classifier performance, we will apply other classifiers in the future. In the future scope of this chapter, we will work with an ECG dataset for heart attack prediction.

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Chapter 7
Assessment of Cardiac Dynamics and Risk Factor Analysis Using Deep Neural Nets

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ABSTRACT

Cardiovascular disease (CVD) is a medical condition that leads to risk of heart disease such as stroke or cardiac arrest. Cardiac attack is a medical condition found in different age groups irrespective of gender. In a clinical study, there are many ways of interpreting the risk factors. The most common risk factors indicating sudden cardiac arrest are glucose, body mass index (BMI), and habitation such as smoking. The difficulties faced by the clinicians are the primary focus of this study. The complexity in clinical stages in examination of medical condition needs to be resolved considering the symptoms and other risk factors leading to sudden cardiac arrests and deaths. Thus, validation of clinical examination at times is a laborious and time-consuming process, while tracking patient history is voluminous over a period of time. This chapter presents the analysis of risk factors causing cardiovascular diseases. The statistical significance and clinical validation of the computer-assisted tool is presented in this study.

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INTRODUCTION

The analysis of risk factors leading to stroke started with a collection of multiple datasets from the Kaggle repository. This dataset consists of twelve variables including the class label, and the presence and absence of stroke. The primary task of the pipeline begins with data wrangling which transforms the raw inputs into a form more suitable for model development, fitting, and evaluation. This stage is followed by exploratory analysis which gives insights into characteristics of features for the extraction of interesting patterns. The pre-processed data was fed into the following baseline models Logistics regression (LR), support vector machine(SVM), Random Forest (RF), Naive Bayes Classification (NB), Gaussian Naive Bayes (GNB), Bernoulli NB, Decision tree classifier (DTC), k nearest neighbor classifier to benchmark the training and test split on the dataset. The proportion of data spitted for train and test split is 80% and 20% respectively. The accuracy score on the classification of presence and absence of stroke is reported using receiver operating characteristics (ROC). The area under the curve will help to report the metrics on classification known as the confusion matrix. When unseen data is fed into the model, the machine learning system will report the following viz, true positives, for those instances where the presence of stroke in the dataset is classified as stroke. Similarly, true negatives are those instances where the absence of stroke in the dataset is classified as no stroke. Likewise, the misclassified instances are reported as false positives and false negatives. The area under the curve shows the performance of the machine on the classification task undertaken. The region under the curve specifies the accuracy, the higher the area covered by the curve higher the accuracy reported by the model. The weakly learned models can be enhanced by boosting the performance individually through an ensemble approach. This includes mixing weak learners, training datasets, and models combined at different levels, known as meta-learners.

Risk factor analysis for Cardiovascular Disease (CVD) is clinically a challenging problem. To address the difficulties of clinical validations of such risk factor analysis, the role of Artificial Intelligence and Machine Learning was recently established. Electrocardiogram (ECG) is the principal source for the examination of cardiac electrical activity (Alfaras Miquel et al, 2019). This modality assists cardiologists for the diagnostic examination of cardiac abnormalities. The profound availability of ECG records has highly motivated us in analyzing cardiac dynamism by classifying the heartbeat using Electrocardiogram (ECG) signals. Recent research findings have reported the significance of unsupervised deep nets in capturing the cardiac dynamics on electrical activity by classifying heartbeats (Moddy et al, 2001). The unsupervised deep convolutional neural nets the variant of one dimensional CNN that has three layers viz flatten, dense, and dropout have shown promising results in the classification of heartbeat (Alfaras Miquel et al, 2019; Armando Fandango, 2018).

The role of Artificial intelligence and Machine learning (AIML) was recently established in the clinical validation of such complex analysis. Artificial Intelligence-based software development tools are highly demanded clinical validations (Aziz et al, 2021). In this perspective, TensorFlow, Python, R, and Data analytics shall play a vital role in developing AI-based tools. The objective of this chapter is to elaborate on the automation of clinical workflow using the primer of AIML concepts in risk factor analysis (Armando Fandango, 2018). Further, this chapter presents the machine learning workflow for the classification of a heartbeat from an ECG signal. Hence this work primarily aims at a classification of heartbeat and augments the machine learning workflow in reporting the anomalies causing the variation in heart rate. The initial phase of this research started with a collection of ECG signals with 15 classes of cardiac dysfunctions from a public source https://archive.physionet.org/physiobank/annotations.shtml under GNU public license. This tool would assist the physicians in Clinical validations and diagnostic examination of cardiac mechanisms. Further, this framework when deployed would possibly replace the manual intervention of ambulatory ECG reports thereby speeding up the clinical workflow. The following section presents the background study on CVD and Electrocardiograms signals. Methodology describing the machine learning workflow is discussed in the next section followed by results and discussion. Finally, the chapter summarizes the work with directions for future work.

Background

Machine learning (ML) frameworks are predominantly employed to devise decision support, clinical workflow automation, and health care analytics for speedy and accurate diagnosis (Celin et al. 2018). This section explains the potential of machine learning in risk factor analysis under the broad spectrum of parametric and non-parametric methods. Supervised learning is a concept of artificial intelligence in the machine learning (ML) paradigm. This concept begins with processing by labeling the dataset which is essential to teach the machine how to learn the features from the datasets and classify them when test data is given to the machine (Aziz et al. 2021; Celin et al. 2018). This concept primarily aims at automating the machine learning workflow for classification in case of multiclass problems and prediction in case of binary class. This paradigm can be broadly classified as (1) Parametric ML and Non-parametric ML. Parametric models include linear regression, logistic regression, Support Vector Classifier, Bernoulli Naïve Bayes (BNB), and Gaussian NB (GNB). The non-parametric models include Random Forest (RF), Classification and Regression Trees (CART), and Decision Trees (DT). A decision tree (DT) is a tree-based machine learning algorithm used for binary classification (Jason Brownlee, 2020a, 2020b, and 2020c). The feature with more information gain is selected for the split decision. The splitting of the dataset is made based on a selected feature whose information gain is high. Random Forest is an ensemble of decision trees classification algorithms. In addition, the performance of models in these paradigms can be well improved by mixing models as done by voting classifiers. In turn, hard voting performs majority voting on the maximum number of instances belonging to a class, while soft voting performs weighted averaging or simple averaging. The specific approach of ensemble design includes a sampling of training data with and without replacement (Jason Brownlee, 2020a). This sampling can improve the model's performance with n sample cross-validation or stratified cross-validation in which the training sample must have a proportion of all the classes. These models augment the performance to improve its classification efficiency. In addition, specific studies have reported the use of boosting techniques like Adaboost, an adaptive gradient boosting algorithm, and XGBoost, extreme gradient boosting based machine learning algorithms for augmenting the performance of ML workflow (Elgendi, 2016a, 2016b, Padmavathi et al, 2015, Kandal et al., 2018, Maciejewski and Dzida, 2018, Clifford and Gari, 2016).

Table 1. Supervised ML models

Supervised Learning	Parameters	Problem Type	Paradigm
Knn	k: The number of neighbors	Classification	Parametric
Random Forest	Estimators, gini index, max_ depth	Classification	Non-parametric
Support Vector Classifier	Radial basis function, regularization	Classification	Parametric
Logistics Regression	Regularization	Prediction	Parametric
Bernoulli Naïve Bayes (NB)	Conditional probability	Classification	Parametric
Gaussian NB	Features assumed to be gaussian	Classification	Parametric
Decision Tree	gini index, max_depth	Classification	Non-parametric

Table 2. Unsupervised models

Models	Methodology	Problem Type	Paradigm
K Means	Centroids	Clustering	Parametric
Feature Selection	Explained variance	Segmentation	Parametric
Principal Component Analysis	Singular Value components	Dimension reduction	Parametric
Linear discriminant analysis	The probability that a new data belong to every class Variance and Mean	Dimension reduction	Parametric
Sammon Mapping	Multi-dimensional scaling	Dimension reduction	Non-Parametric

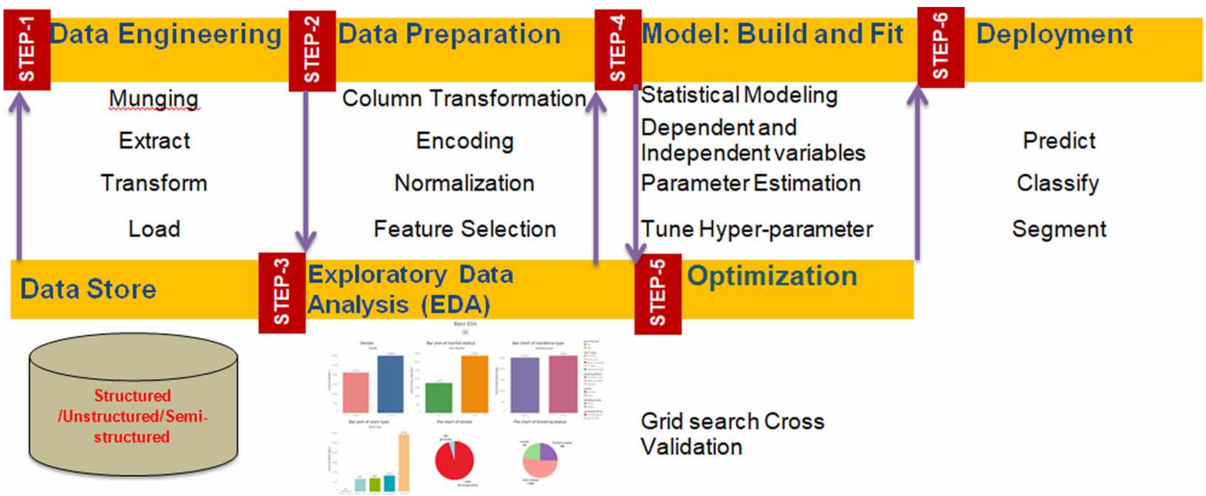
Table 3. Ensemble technique

Models	Methodology	Problem Type	Paradigm
Voting Ensemble	Max Voting	Classification	Parametric and Non-parametric
	Averaging and weighted averaging	Prediction	Parametric and Non-parametric
Boosting	Residual error	Classification	Non-Parametric
	Gradient descent error	Prediction	Non-Parametric
Bagging	Samples with replacement,	Classification	Non-Parametric
	without replacement		Non-Parametric
Stacking	Meta learner	Classification	Non-Parametric
Homogeneous and Heterogeneous	Voting and Meta-learning	Classification and Prediction	Non-Parametric

METHODOLOGY

The various algorithms in the literature have described the potential of machine learning tasks in feature selection, training and model fitting, evaluation, and hyper-parameter tuning. The performance of classification algorithms is evaluated using metrics such as precision, recall, sensitivity, specificity, and accuracy (Jason Brownlee, 2020b, and 2020c). The parametric and nonparametric machine learning paradigm is explained in tables 1, 2, and 3.

Figure 1. Block diagram of Machine Learning (ML) Workflow



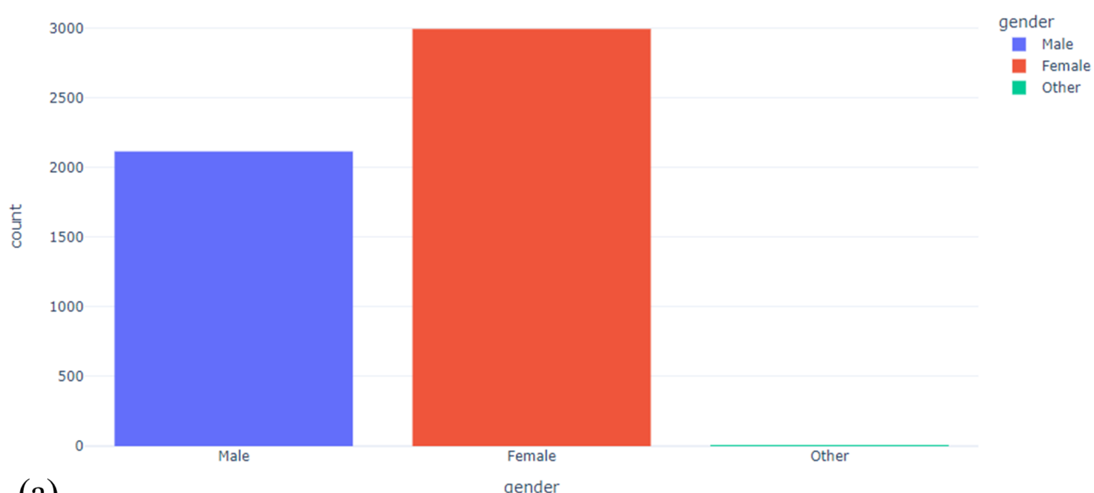
The series of tasks involved in the machine learning pipeline as shown in figure 1 are as follows:

1. Data Engineering
2. Data Preparation
3. Exploratory Data Analysis
4. Model Build and Fit
5. Optimization
6. Deployment

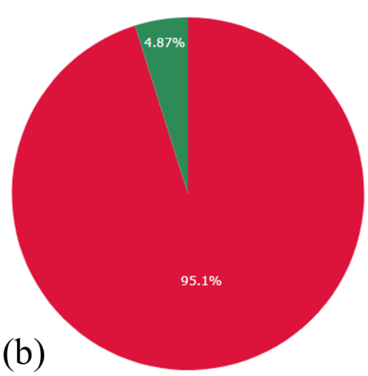
Table 4. Data dictionary

Variable	Type	Description
Id	int	unique identifier
age	float64	age of the patient
gender	object	"Male", "Female"
hypertension	int64	0 if the patient doesn't have hypertension, 1 if the patient has hypertension
heart_disease	int64	0 if the patient doesn't have any heart diseases, 1 if the patient has a heart disease
ever_married	object	"No" or "Yes"
work_type	object	"children", "Govt_jov", "Never_worked", "Private" or "Self-employed"
residence_type	object	"Rural" or "Urban"
Average_glucose_level	float64	average glucose level in blood
Bmi	float64	body mass index
Smoking_status	object	"formerly smoked", "never smoked", "smokes" or "Unknown"*
stroke	int64	1 if the patient had a stroke or 0 if not

Figure 2. Risk factor analysis in Patient Cohort



(a)



4.87% of patient cohort has stroke

(b)

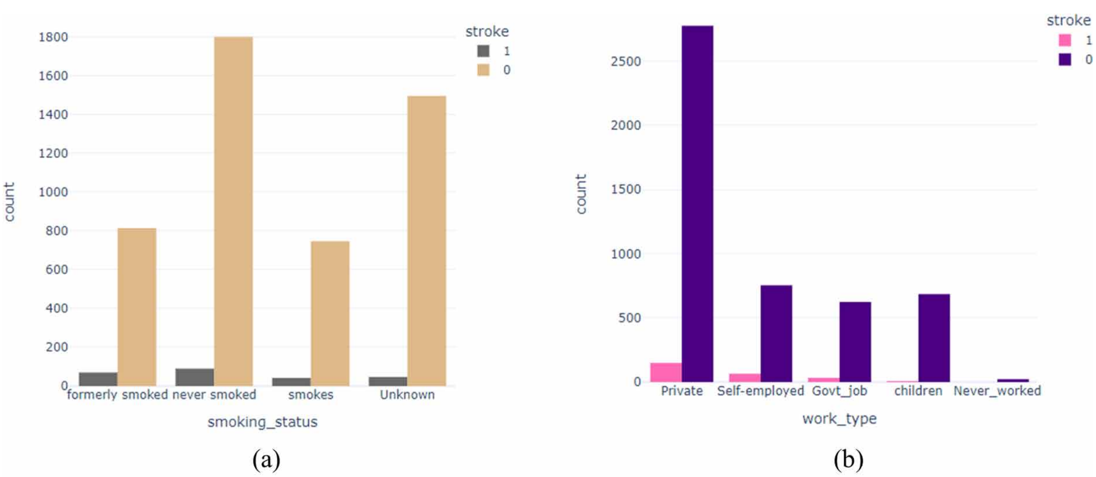
DATASTORE

The Datastore is the repository of samples collected from patient cohorts. This repository contains the information about samples collected from clinical sources. In this study, biological variables are considered for the analysis of risk factors. Eventually, social factors also contribute to the risk in addition to the biological features in the assessment of risk factors leading to stroke. The input features considered for the risk factor analysis are Patient id: which is a unique identifier of the biological features such as age, gender, hypertension, average glucose level, body mass index (BMI), the history of heart disease, the presence, and absence of stroke which is a binary class which is the target variable or label assigned to the instance of the patient cohort. The distribution of stroke and gender is reported in figure 2. The social factors are marital status, occupation type, kind of living environment as residence type, the habits such as smoking. The data dictionary identified and used for EDA is shown in Table 4.

DATA ENGINEERING

Data engineering is the systematic process of transforming the features variables that are necessary for the representation of variables in training the machine so that the machine can make an accurate prediction on the unseen data. The following analysis is made to identify the characteristics of each feature variable based on the distribution of the dataset. The results are illustrated as graphical plots that visually represent the trends, grouping, and correlation using appropriate statistical measures. The kinds of analysis that can be interpreted visually are social factors as follows with respect to the age and gender of cohorts. The Social factors are 1. Smoking status 2. Work type 3. Residence Type

Figure 3. Patient cohort considering the social factor: (a) Smoking status Risk factor (b) Work-type

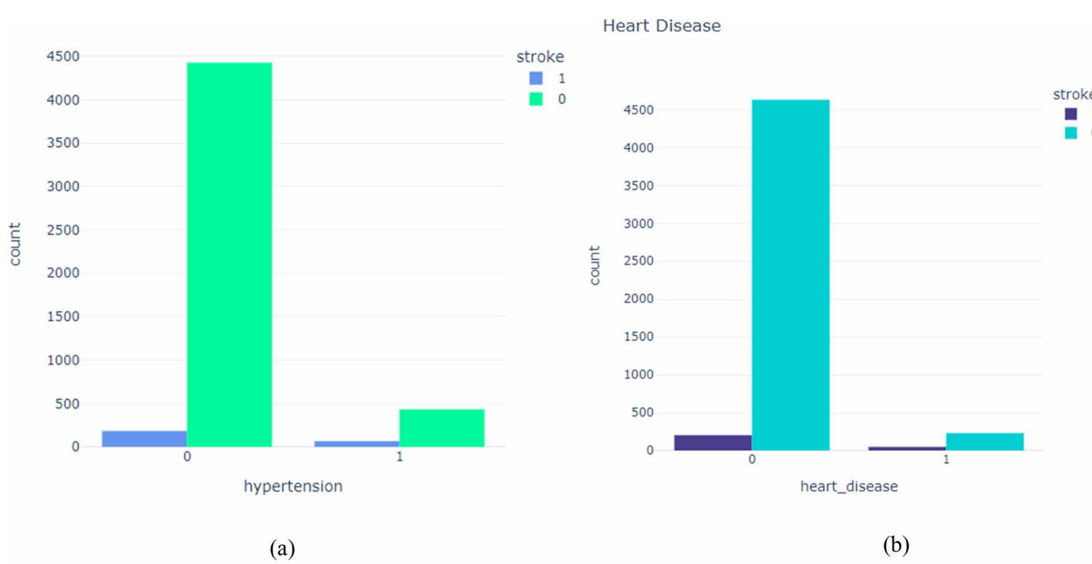


(a) (b)

The count on the distribution of stroke among the individuals is analyzed using histogram plots. The categories of individuals are formerly smoked, never smoked, and smoked. The histogram plots based on smoking status are shown in figure 3.a. The next analysis is to count the distribution of stroke among the individuals based on work types like private, self-employed, government sector, never worked as shown in figure 3.b. In this cohort study of 5110 patients, the number of cases with no smoking history is found to be high compared to unknown status and formerly smoking status. The risk of stroke is less in this patient cohort as seen in figure 4.a the distribution with respect to gender, similarly, it is found less with respect to residence type as seen in figure 4.b. The presence of stroke is denoted as 1 and absence as 0.

Figure 4. Stroke Distribution: (a) Gender (b) Residence Type

Figure 5. Stroke Distribution: (a) Hypertension (b) Heart disease



The following section presents the exploratory data analysis of the patient cohort considering the biological variables such as age, gender, average glucose level, hypertension, etc. Exploratory Data Analysis is essential to identify patterns, and anomalies and get insights to form a hypothesis for a better understanding of the data. Feature selection is done based on statistical hypothesis using the sklearn (scikit) library. Data pre-processing is done to check for any missing values, noisy data, or other inconsistencies before the execution of the algorithms. It is found that the BMI attribute contains 201 null values. So, to balance the NA values the missing values in the column, have been filled with their mean values. Bar plot of gender, hypertension, and any history of heart disease effect on stroke: It can be seen from figure 5 that although both male and females are not hugely affected by stroke, the male population have a higher chance of risk than females. Further age, average glucose level, BMI, and their relation with a stroke can be analyzed using density distribution plots, the area of overlap in each density plot describes the relationship between the biological variable considered in the analysis for risk of stroke in patient cohorts. The cohorts affected by stroke are illustrated by the total area of the overlapping regions as seen in figures 6 and 7. The distribution of stroke with respect to body mass index (BMI) and average glucose level is found to be similar as is evident from the area covered by the overlapping regions in density plots.

Figure 6. Stroke Distribution in patient cohort with respect to age

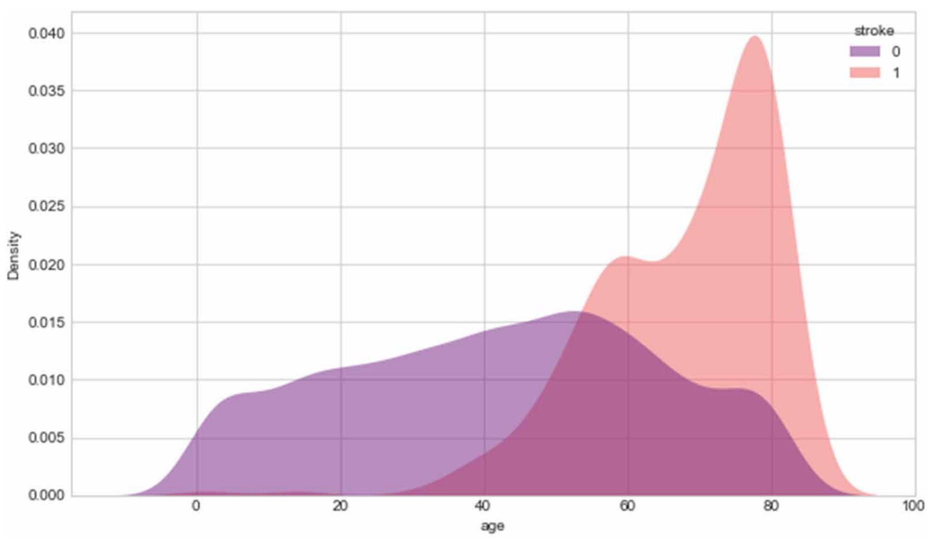


Figure 7. Stroke Distribution: (a) BMI (b) Average Glucose Level

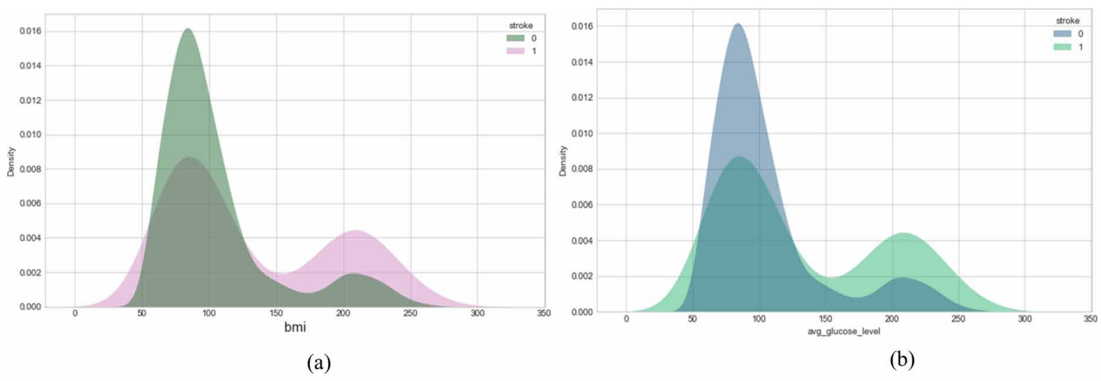


Figure 8. Correlation plot

The heat map shown in Figure 8 is plotted between the independent features and target variable using the *seaborn* library in python. This plot gives a clear visualization of how closely two features are related or affected by each other. It is evident from the correlation plot that the features such as BMI, hypertension, and heart disease are considered to be important biological factors. The following graphical plots explain the distribution of heart disease in the patient cohort with respect to hypertension.

Figure 9. Distribution of hypertension in patient cohort

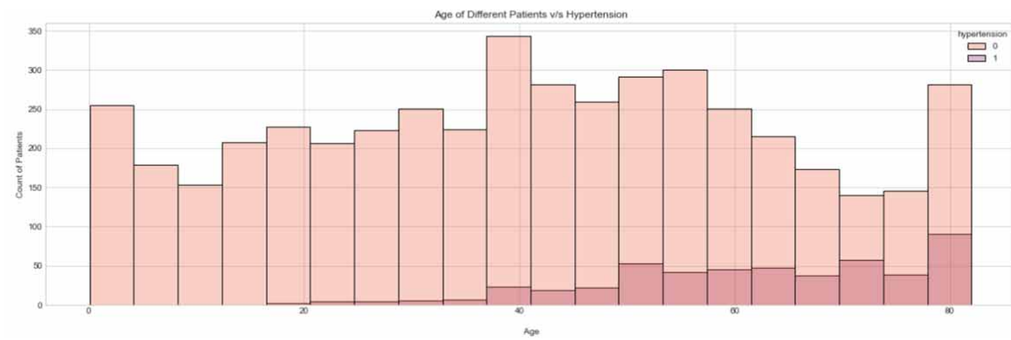


Figure 10. Distribution of heart disease in patient cohort

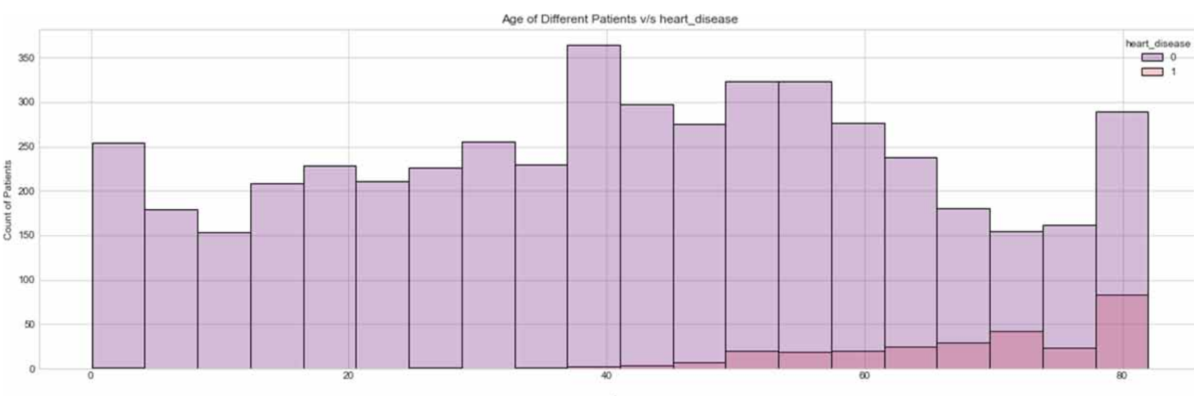
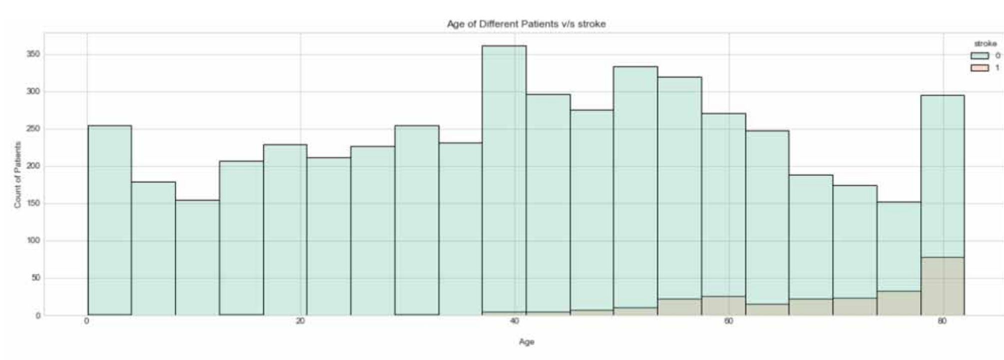
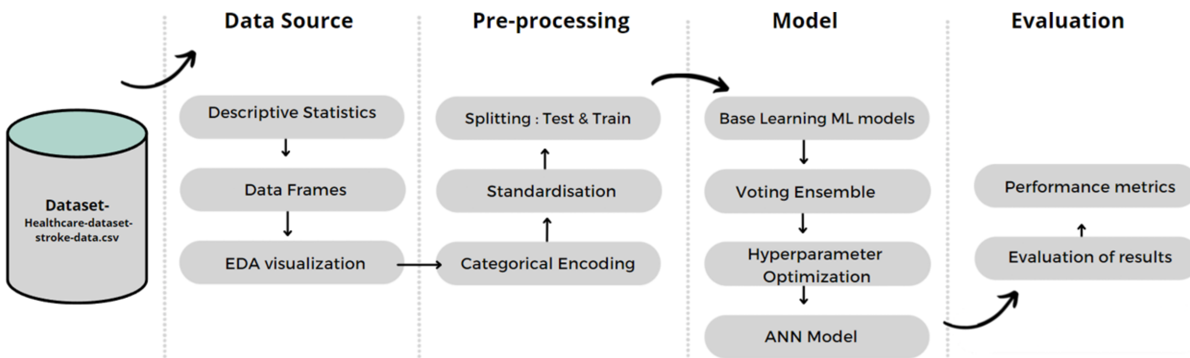


Figure 11. Distribution of heart disease in patient cohort



Hypertension is found to be increased in the age group between 40 and 80. The distribution of hypertension based on the aging of individuals is shown in figures 5 and 9. The patients in the age group of 80 have a high risk of heart disease compared to others. It is found that heart disease risk is experienced among the group of an individual between 40 and 80. It is inferred from figures 9 to 11 that hypertension and heart disease have the risk of stroke. The count of a patient with the presence of risk for cardiac arrest is analyzed as seen in figure 11. The presence of stroke is found to increase concerning age in patient cohort. It is essential to analyze the distribution of stroke with respect to age as biological factors in humans tend to react concerning age. Hence, the severity of stroke will vary under various biological factors like age, hypertension, and history of heart disease as is evident from figure 10. The trend in heart disease and stroke is found to be similar with respect to age in Figures 10 and 11. Hypertension in the cohort is seen in figure 9. The trend in the risk of stroke and heart disease is found to begin at the age of 40 in patient cohort while the hypertension feature of the study shows the risk may arise at the age even below 40. The significance of EDA is well noted in the figures 9 to 11 in understanding the risk factors and severity of the biological factors in patient cohort.

Figure 12. Machine learning workflow



MODEL FORMULATION

Machine learning workflow in cardiovascular risk factors involves a pipeline. The flow of work in the pipeline is illustrated in figure 11. The data source is a comma-separated value from the public repository hosted by healthcare centers, government organizations, hospitals, etc. The input dataset is analyzed to infer the statistical significance of each feature present in the dataset. The exploratory data analysis described in the previous section demonstrates the significance of statistical measures and the relationship between the features. This step leads to data pre-processing steps where categorical variables such as residence type, work type, marital status, and smoking status are transformed using encoding methods to represent the data suitable for machine learning. Data preparation for the machine learning process involves two steps (1) Separation of independent and target variables based on stroke distribution in patient cohort. (2) Separation of the dataset into train and test as a measure of 80% and 20% respectively (Armando Fandango, 2018). The parametric (linear) and non-parametric (non-linear) models are fitted for the analysis of biological and social factors leading to stroke. These models are (1) Logistic regression (2) Gaussian Naïve Bayes (NB) (3) Bernouli Naïve Bayes (BNB) (4) k Nearest Neighbors (5) Support vector Classifier (SVC) (6) Decision Tree Classifier (DT) and (7) Random Forest (Alfaras Miquel et al, 2019; Jason Brownlee, 2020a). The primary analysis is made without tuning the parameters and appended to a list for metric comparisons. The receiver operating characteristics (ROC) metrics shows the plot between true positive hit rate and false-positive hit rates. It is seen from the ROC plot in figure 13 that naïve learner k-nn has the least accuracy followed by SVC. However, the performance of BNB and GNB is higher compared to k-nn. To enhance the performance of base classifiers, an ensemble approach is adopted in which voting Classifier using hard voting of base learners are used and the performance is further improved by tuning the hyper-parameters using optimization by Grid search cross-validation.

Feature Selection

Features considered for the analysis of heart disease risk can be considered for reducing the dimension using supervised linear transformation technique, Linear Discriminant Analysis (LDA), and feature selection are applied using the best_params_ property of *gridsearchCV* which gives the result on the best-suited parameters for the model. Scikit-learn provides *SelectKbest()* class for extracting the best features from the dataset. The SelectKBest method selects the features according to the k highest score. By changing the *'score_func'* parameter we can apply the method for both classification and regression data. The f-scores of all the features are shown after applying the feature selection. Here the f-score reveals the discriminative power of each feature independently from others. Selecting the best features is an important process as it helps to eliminate the less important part of the data and reduce training time. The threshold score is set to be greater than 50 for selection.

The mean and variance of classes and the probability that new data belongs to each of the classes in the datasets are ensured with LDA. In practice, linear algebra operations are used to calculate the required quantities efficiently via matrix decomposition. With all the above steps, the new feature set of X and y is trained for each tuned base learner and the results are stored for each model. In comparison to the model before tuning, feature selection, and LDA, it is noticeable that although the *gridsearchCV* doesn't improve the results to a great extent, selecting the important features increases the performance of the models tremendously. We can see a clear improvement in the score for the Naive Bayes model (both Gaussian and Bernoulli) with a significant rise from 37% to above 93% on performing LDA and *gridsearchCV*. Further, some of the other models such as SVM, and XGBoost RandomForest classifiers also show a slight increase in their performance. The accuracy of machine learning models developed using the sklearn machine learning module is reported in table 5.

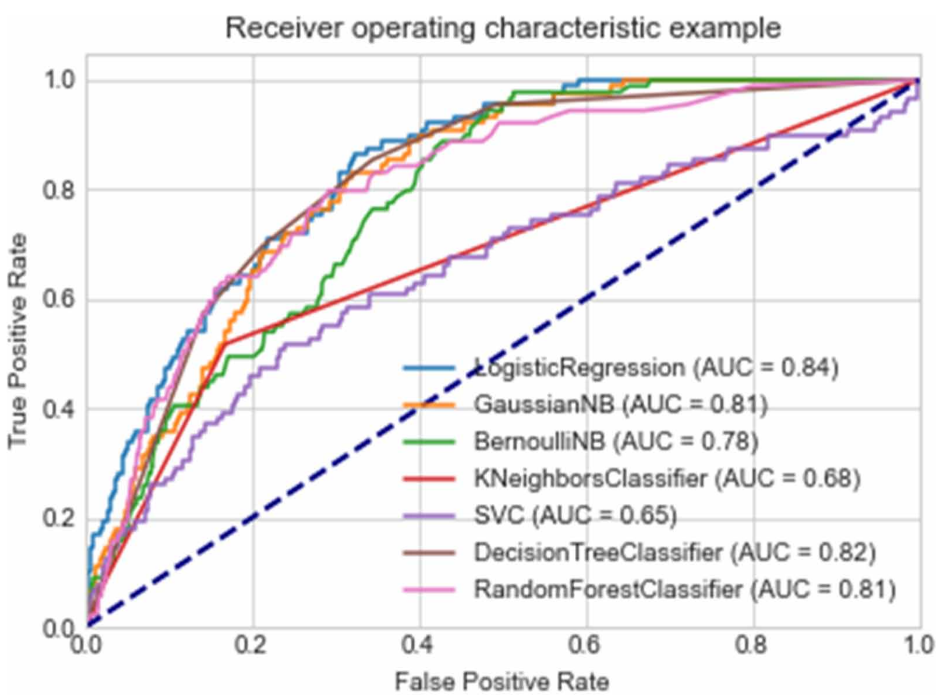
ARTIFICIAL NEURAL NET (ANN)

The computational framework of ANN is defined by input- hidden-output neuron computation. The **Input layer:** Accepts input of different formats, **Hidden layer:** The input goes through some transformation using the hidden layer with some weighted sum of inputs including the bias, **Output layer:** The input goes through a series of transformations using the hidden layer, which finally results in output that is conveyed using this layer. With the fitted ANN model, we classify the results such that if the predicted y (stroke presence or absence) is greater than 0.5 then it is appended as 1, if less than 0.5 then it is 0.

Table 5. Sklearn module for Machine learning: Accuracy Report on Patient cohort

Model	Concept	Accuracy	Sklearn Machine Learning Module
Bernoulli Naïve Bayes (BNB)	statistical learning	0.78	stroke, the target is classified based on the conditional probability of features
Gaussian NB	statistical	0.81	Feature likelihoods are assumed to be gaussian
Support Vector Classifier	parametric	0.65	Regularization metrics with radial basic kernel
Random Forest	non-parametric	0.81	estimators based on hyperparameter
knn classifier	instance-based learning	0.68	k neighbors
Decision Tree (DT) classifier	non-parametric	0.82	information gain and gini index
Logistic Regression	binary classification	0.84	stroke, the target is predicted based on the sigmoid function for a binary class problem

Figure 13. Receiver operating characteristics (ROC) of ML models



The intensive computation of ANN at different layers makes ANN a slightly better model than the voting ensemble on-base learners. Of note, hyper-parameter tuning and feature selection for the voting ensemble produced a score equivalent to the ANN model. The more important features that decide the risk of heart stroke using feature selection are found to be age factors, marital status, heart disease history, hypertension, and the average glucose levels. Generally, tests are categorized based on the area under the ROC curves. The closer the curve is to the True Positive rate (upper left corner), the better is the model. From figure 13, it can be analyzed that except for the SVC and Bernoulli Naïve Bayes model curves, all the others give a significantly good result among the base learners.

Assessment of Cardiac Dynamics Using Electro Cardiogram – A Case Study

Cardiovascular disease can be examined primarily from the clinical study using the report electrocardiogram (ECG) (Weimann et al, 2021). This can ensure the premature finding of heart disease and the proper selection of the patient's customized treatment. However, the detection of arrhythmia is a challenging task to perform manually (Elgendi, 2016a, 2016b, Padmavathi et al, 2015, Kandal et al., 2018

Maciejewski and Dzida, 2018, Clifford and Gari, 2016). In event of risk factor analysis, automated detection of the type of heartbeat is a necessary technique. The test results have been reported to successfully categorize arrhythmia with an overall accuracy of ~96%. The continuous arrhythmia beats become fatal. However, a single arrhythmia heartbeat may not have a serious impact on life (Alfaras Miquel et al, 2019; Armando Fandango, 2018; Celin et al, 2018).

The model is formulated using three pairs of Convolution1D-MaxPool1D layers followed by a Flatten layer that reduces the values to 1D and three dense layers, two of which have ReLU activation function while the last layer has 5 nodes, corresponding to the 5 output class labels, with a Softmax activation function. The model was able to achieve ~96% accuracy on the test dataset (Aziz e al, 2021). Therefore a deep learning 1-D CNN is essential for the automatic ECG heartbeat categorization to categorize five different types of cardiac arrhythmia. The proposed ECG heartbeat classification systems performance was validated from Physionet's MIT-BIH Arrhythmia Dataset. Furthermore, the suggested ECG arrhythmia classifier can be applied in several biomedical applications such as a medical robot that monitors the ECG signal and assists the medical experts to detect cardiac arrhythmia more accurately. As part of our future work, our framework will be extended by implementing 2-D CNN with ECG greyscale image input which will be transformed from the MIT-BIH Arrhythmia Dataset ECG recording. The common types of heartbeats classified from ECG signals are

(1) Non-ectopic beats (normal)
(2) Supraventricular Ectopic Beats
(3) Ventricular ectopic beats
(4) Ectopic beats - Atrial Fibrillation
(5) Fusion beats
(6) Unknown beats

Non-ectopic beats are normal heartbeats. Ventricular ectopic heartbeats are of type TachycardaExtra. This kind of abnormal heartbeat begins in one of the heart's lower chambers known as Tachycardia. It is commonly seen that premature ventricular contractions (PVCs) occur in most people at times. The causes of such heartbeats include alcohol, certain medications, illegal drugs, caffeine, tobacco, or anxiety (Kandal et al., 2018, Maciejewski and Dzida, 2018, Clifford and Gari, 2016).

Figure 14. Supraventricular ectopic beat

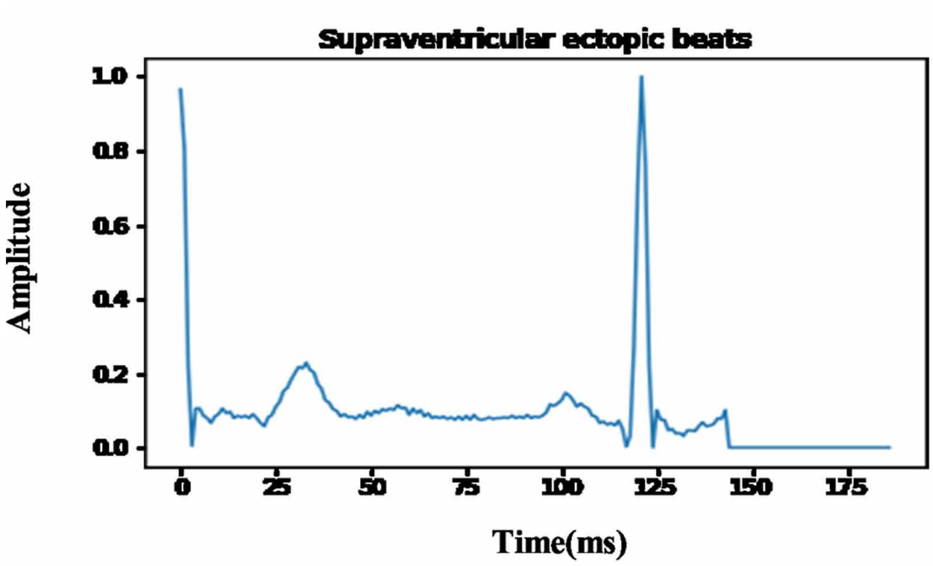


Figure 15. Non-ectopic normal beat

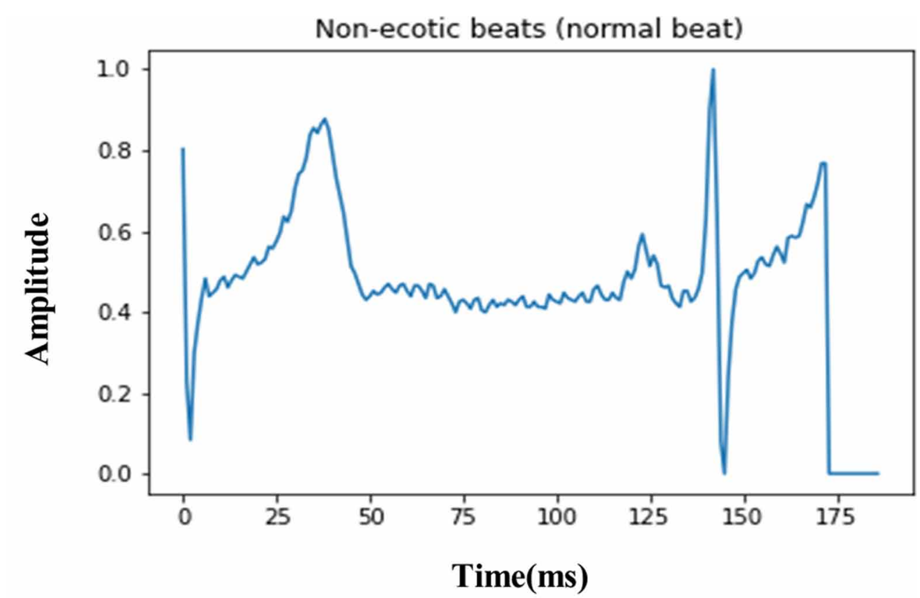


Figure 16. Ventricular ectopic beat

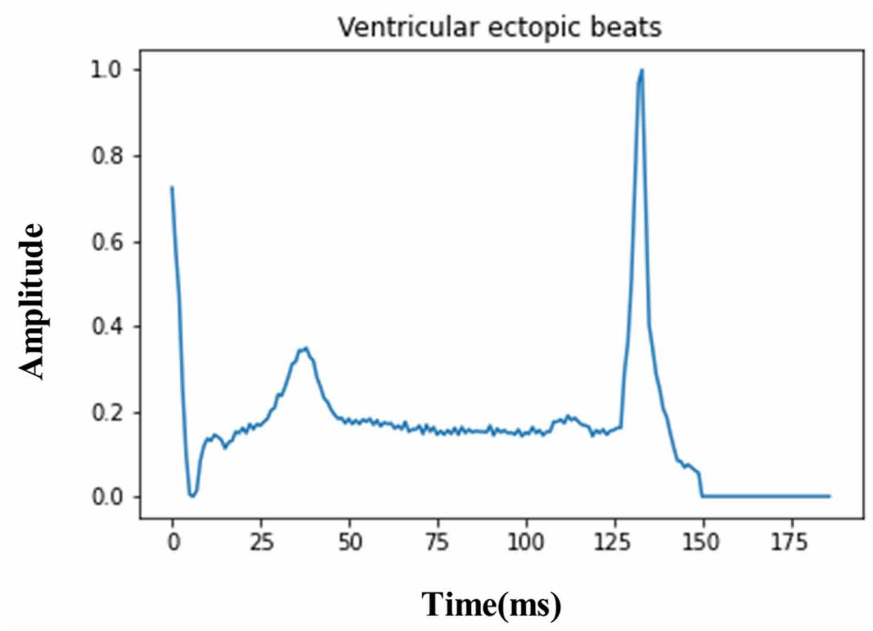


Figure 17. Fusion beat

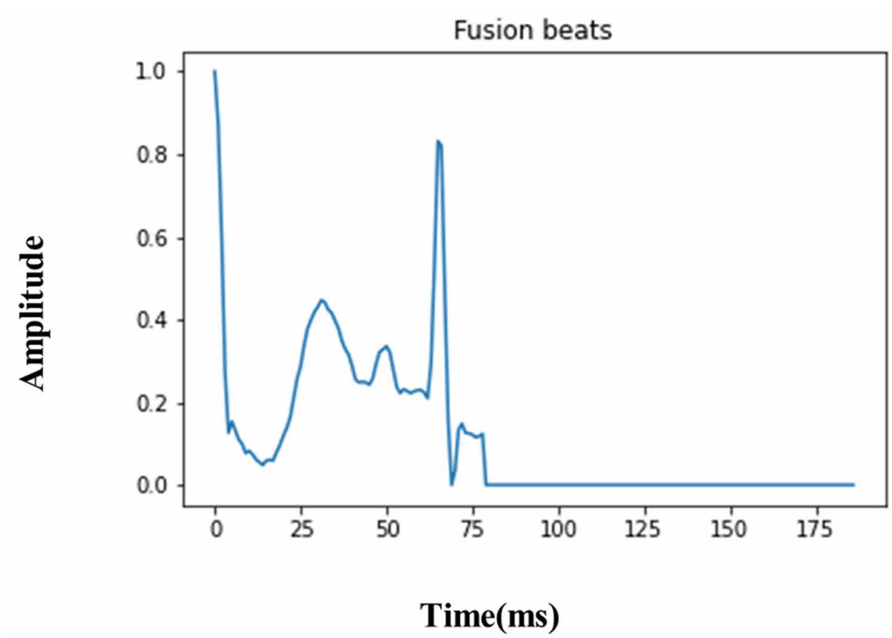
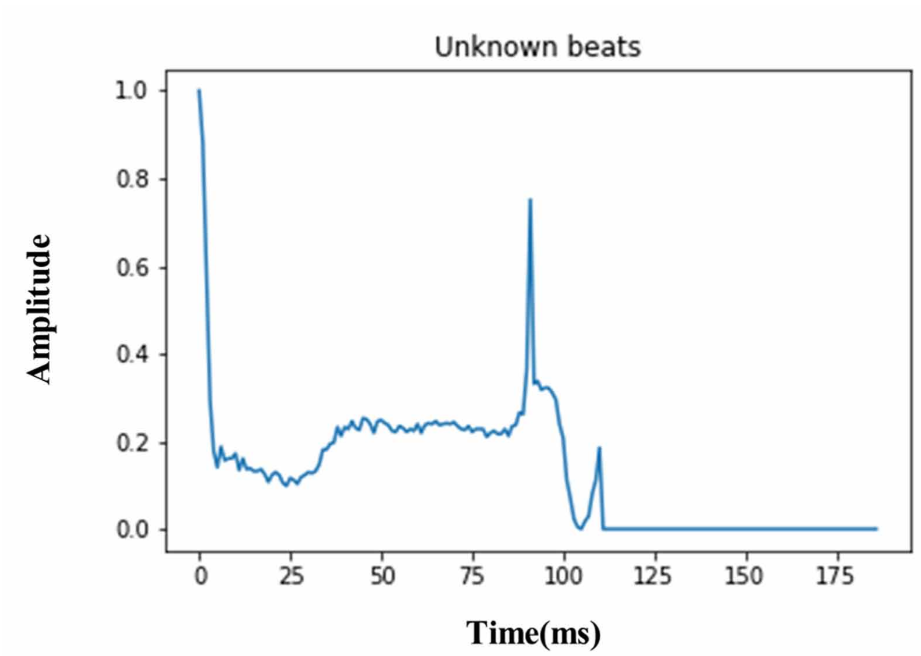


Figure 18. Unknown beat



The symptoms of PVCs are skipped-beat sensations in the chest. However, PVCs occurring for a long time continuously more than 30 seconds is considered a potentially serious cardiac condition known as ventricular tachycardia. The normal beat is seen in figure 15. This can be compared with supraventricular type as seen in figure 14. A kind of abnormal heartbeat, Supraventricular is of type Tachycardia. It is a faster than the normal heart rate that begins above the heart's two lower chambers. It normally develops as electrical impulses of the heart, if disrupted, it is considered a rapid heartbeat. A patient may or may not have symptoms at times. The most common symptom is cardiac palpitations. Certain manoeuvres, medications, an electrical shock to the heart (cardioversion), and catheter-based procedures (ablation) can help to slow the heart. The ventricular ectopic beats are shown in figure 16. Another kind of symptom experienced by a patient has skipped heartbeat which is ectopic or atrial fibrillation. The different kinds of arrhythmia identified from the classes of heartbeat are shown in figures 14 to 18. A deep convolutional neural net is designed to train these classes of heartbeats to classify the unseen heartbeat. The following section describes the formulation of a convolutional neural network (CNN).

Convolutional Neural Network

Convolution Operation

Let g_l^k be the convolution operation such that

$$g_l^k(u,v) = \sum_e \sum_{i,j} h_c(i,j).e_l^k(p,q) \tag{1}$$

Where $h_c(i,j)$ is an instance of the input tensor image H_C, which is an instance-based product with $e_l^k(p,q)$ index of the k^{th} convolutional kernel k_l of the l^{th} layer. The output feature map of the k^{th} convolutional operation can be represented as

$$\mathbb{G}_l^k = \left[g_l^k(1,1), \ldots.., g_l^k(u,v), \ldots., g_l^k(U,V) \right].$$

The convolution operation is shown in Eq.1.

Pooling Operation

Let the feature map be $\mathbb{Z}_l^k$ for l^{th} layer such that the pooled feature is given as follows,

$$\mathbb{Z}_l^k = f_p\left(\mathbb{G}_l^k\right) \tag{2}$$

The pooled feature map is represented as $\mathbb{Z}_l^k$, that represents the pooled feature map of the l^{th} layer for the k^{th} input feature map $\mathbb{G}_l^k$, where f_p defines the type of pooling operation. The use of pooling formulation in CNN is acknowledged by various researchers. The pooling operation is shown in Eq.2.

Decision Function

The intrinsic feature maps are learned by the decision function, also known as the activation mechanism. The learning process is accelerated based on the selection of appropriate activation functions. The convoluted feature is activated by mapping the feature convolution using the activation function defined in Eq.3.

$$\mathbb{D}_l^k = f_a\left(\mathbb{G}_l^k\right) \tag{3}$$

The output of a convolution is given by $\mathbb{G}_l^k$ that is passed to the decision function f_a which is a non–linear and returns $\mathbb{D}_l^k$, the transformed l^{th} layer output. The most common activation function used to overcome vanishing gradient is ReLU shown in Eq.4. The sigmoid activation is shown in Eq.5

$$ReLU = \begin{cases} 0 \ if \ x \le 0 \\ x \ if \ x > 0 \end{cases} \tag{4}$$

$$Sigmoid = \frac{x}{1+e^{-x}} \tag{5}$$

Normalization

The feature maps are corrected from internal covariance using Eq.6.

$$\mathbb{N}_l^k = \frac{\mathbb{G}_l^k - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}} \tag{6}$$

where for a batch process the normalized feature map is $\mathbb{N}_l^k$, input $\mathbb{G}_l^k$ the feature map, the mean μB, and the variance σ_B^2. The use of ε is to nullify division by zero.

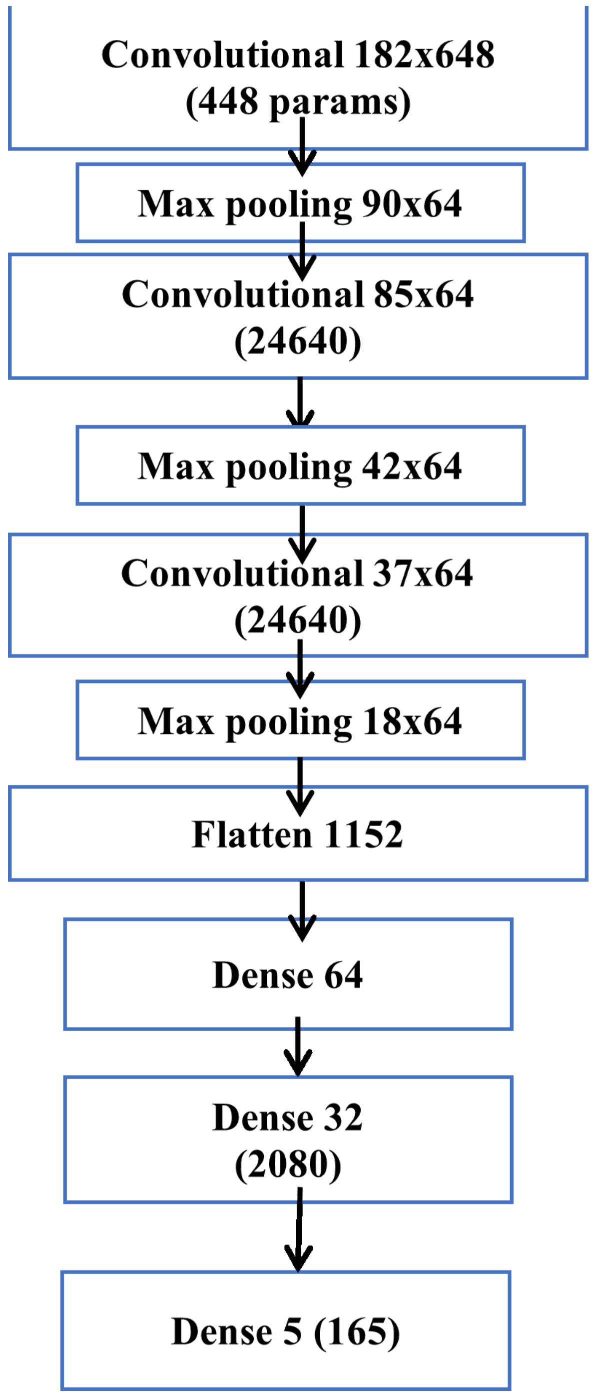
Dropout

Dropout is required to improve the generalization by randomly skipping connections based on probability. This mechanism helps in augmenting the network topology by randomly dropping the connections to result in thin layered network architecture.

Fully Connected Layer

The input from feature extraction stages and output of all preceding layers are analyzed globally. Thus, a non-linear combination of the feature set is selected and used for the classification process.

Figure 19. Deep convolution neural nets model architecture



The basic CNN architecture describing the convolutional operation, pooling, and activation functions is shown in figure 19. The CNN unit is defined with three convolutional and Max pool layers in sequential order. This is followed by flattening to reduce the dimension of the features available in pooling layers.

Finally, the unit is terminated by the fully connected network with dense layers of 64, 32, and 5 at the end of the layer. The sample class used for training the CNN is shown in table 6. The distribution of classes of ECG signals is shown in figure 20. These classes are used to train the CNN shown in figure 19. The input dimension is 87554 to produce 5 classes of output. It is clear to understand from figures 20 and 21 that there is a class imbalance problem in the dataset. Hence, to increase the sampling of signals during training signals are augmented to cover the ECG amplitude to overcome class imbalance cases during testing on unseen ECG signals. The workflow shown in figure 19 has a sequential flow with three sets of the convolutional layer with an input resolution of 182x648 and max-pooling with 90x64 followed by convolutional layer 85x64 and max-pooling with 42x64, the third set of the convolutional layer with second sequential input.

Figure 20. ECG Signals: Total instance in each class of heart beat

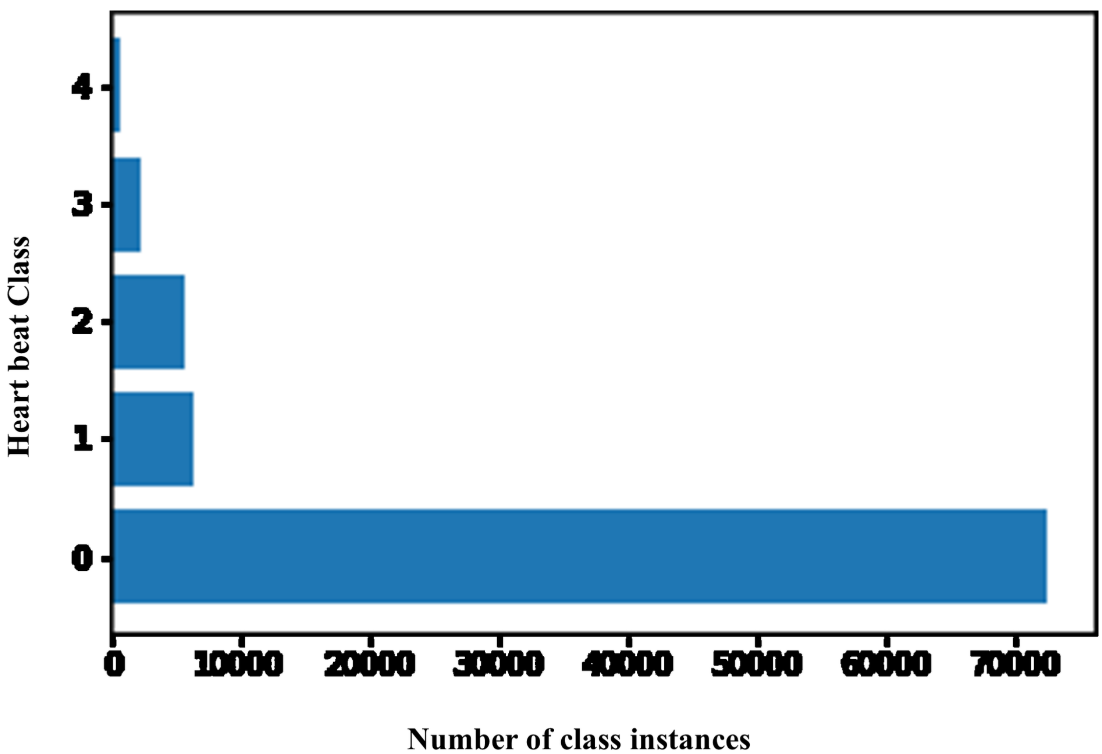


Table 6. ECG Signal Class Sample

Input: Observations	87554	
Output:	5 classes	
Dimension:	87554, 188	
Train	250000	
Test	21892	
Heartbeat Type	Class	Instances
Non-ectopic beats (normal beat)	0	72471
Supraventricular ectopic beats	1	2223
Ventricular ectopic beats	2	5788
Fusion beats	3	641
Unknown beats	4	6431

In a cohort study on ECG signals, it is necessary to consider the case of class imbalance, a case where the number of instances in each of the candidate classes may not be sufficient or zero. These cases need to be handled sensitively to avoid misinterpretation of unseen ECG signals and also to avoid overfit and underfit of the model with respect to training and validation loss which is illustrated in figure 22 and the corresponding accuracy score as illustrated in figure 23.

Figure 21. ECG Signals: Class percentage of the type of heart beat

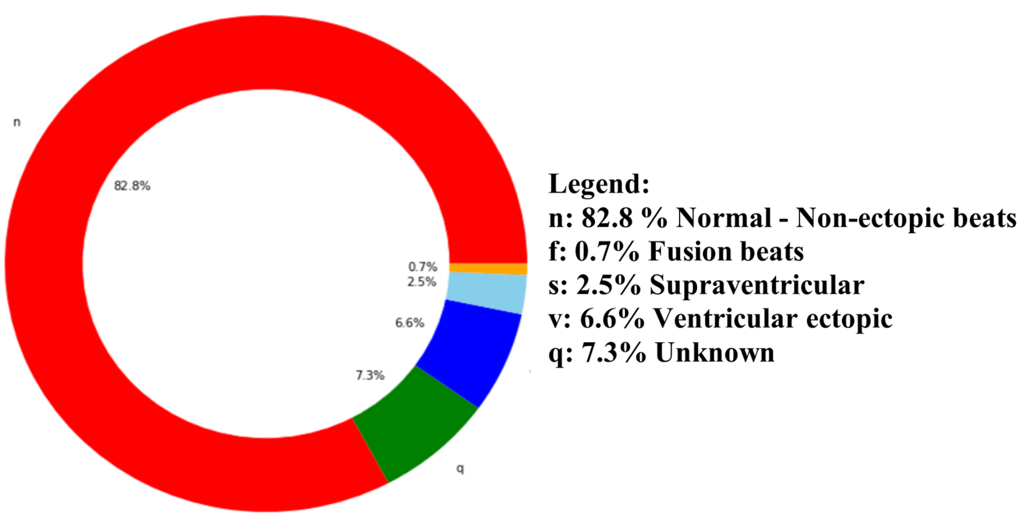
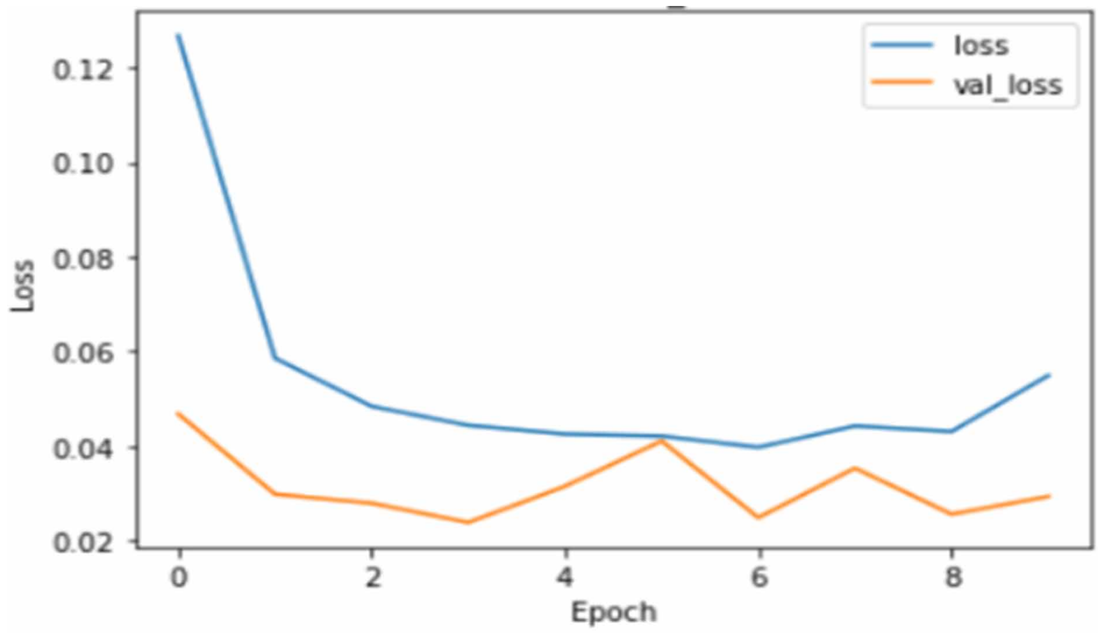


Figure 22. Loss versus Epochs

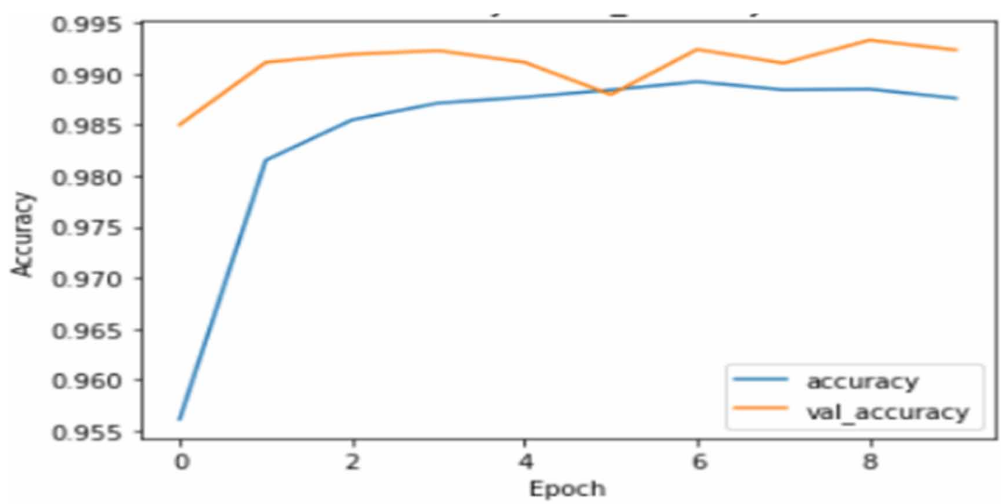


It is evident from figure 22 that the training loss descends with an increase in the number of epochs which is the loss due to the training sample. The deep neural net is tested to execute at various epochs. The loss at every epoch is examined and trained the CNN when the loss is minimal. The different classes of ECG signals are named as n: normal: non-ectopic beats, f: fusion beats, s: supraventricular beats, v: ventricular ectopic beats, and q: unknown beats. The validation accuracy is below training accuracy, the model is slightly over-fitted as it is not that significant. Training loss shows improvement in learning. The model can be tested by turning the models for better accuracy on the validation set. It is seen from the figure 21 normal non-ectopic beats are at the higher count of the training sample say 82.8% compared to 0.7% of fusion beats which is found to be very low in count compared to normal ectopic beats. The supraventricular ectopic beats are 2.5% compared to the higher count of 82.8% normal ectopic beats. The fusion beats are found to be 0.7% which is very less compared to other classes such as supraventricular beats, ventricular ectopic beats, and unknown beats. The datasets contain 7.3% of unknown beats as seen in figure 20. Thus, a class imbalance problem arises with this dataset. Of note, this class imbalance needs to be resolved before formulating the model. The training and validation loss at every epoch is shown in figure 22. It is found that validation loss is less compared to the training loss. A very low loss is estimated at each epoch. This is achieved in practice when augmented with additional signals whose amplitude is the same as the observed ECG signals.

The augmented ECG signals are resampled to improve the model settings. The sampling rates of these signals are tested for loss. It is seen in figure 22 the validation is much less compared to training loss. Thus, data augmentation is necessary so as to reduce the randomness of the model with respect to bias and variance. This confirms the significance of augmenting ECG signals to report the classification results of the type of heartbeat when an unseen ECG signal is fed to the model. The initial training accuracy was found to be 95.5%. To improve this accuracy score, the model is trained at a reasonable number of epochs. There is a gradual increase in accuracy score at initial epochs and it remains at 98.7% after epoch 2 and remains the same at all succeeding epochs. The scenario is different from invalidation accuracy. There arises a case where test and train accuracy meets the same.

The initial epochs show a classification accuracy score of 98.5% and are found to be in the same range even when epochs are increased as seen with the training set in figure 23. The test accuracy is found to vary between 98.5% and 99.4%. Eventually, it is necessary to consider the feature variable when challenges are experienced in streamlining the machine learning pipeline especially when data from different sources are combined. The challenges experienced by the developers in combing the ECG datasets from "Massachusetts Institute of Technology-Beth Israel Hospital" and data source developed by "Physikalisch-Technische Bundesanstalt (PTB)", the National Metrology Institute of Germany, https://www.physionet.org/ are lack of candidate class instances for each class of arrhythmia. PTB dataset is pre-processed to consider the different classes of arrhythmia that are segregated into two classes normal and abnormal.

Figure 23. Accuracy versus Epochs



FUTURE RESEARCH DIRECTIONS

The study describing biological and social factors influencing cardiac arrests needs further investigation on how features like age, gender, and hypertension are influencing stroke in a patient cohort. The vast availability of observations in the patient cohort has highly motivated the authors to build a machine learning model to infer the relationship between social and biological features (Moddy et al, 2001, Elgendi, 2016a, 2016b, Padmavathi et al, 2015, Kandal et al., 2018). Further, it is necessary to highlight the significance of parametric and non-parametric formulation of machine learning algorithms to infer the statistical significance of the machine learning model in clinical validations. The importance of EDA is analyzed in every data science task described in this cohort study (Clifford and Gari, 2016, Kandal et al., 2018, Maciejewski and Dzida, 2018, Padmavathi et al, 2015). However, the correlation between social factors viz., work type, residence type, and biological features viz., age, gender, hypertension, and average glucose level need to be investigated to select the right formulation of the model (Maciejewski and Dzida, 2018).

The social factor of smoking status influencing stroke as seen in this cohort study has statistical inference. However, the relationship between social and biological factors influencing stroke, heart diseases, and cardiovascular disorder is still in nutshell. This can be resolved by cohorting, a clinical study over time in a group. Recent years have shown progress in the study of coronary x-ray angiograms, and the study of cardiovascular structures using x-ray angiograms (Maciejewski and Dzida, 2018). These datasets are enriched with ground truth about the structure of blood vessels in left and right proximal coronary arteries. The lesion on right and left coronary arteries are marked by a cardiologist for the classification of blood vessels. A syntax score is arrived at based on the medical condition examined by the physician. The diagnostic procedures for interventional catheters are thus decided based on clinical studies of biological and social factors influencing stroke (Clifford and Gari, 2016, Maciejewski and Dzida, 2018). Thus, it is necessary to leverage the machine learning technologies on X-ray angiograms in a larger cohort so as to control the death due to sudden cardiac arrest.

CONCLUSION

The biological and social factors influencing cardiac arrest are the prime focus of this chapter. In the context of computer-aided diagnosis using AIML, this chapter presented a machine learning workflow in risk factors analysis of cardiovascular disease (CVD). The importance of exploratory data analysis to a data scientist is illustrated with a case study on risk factors analysis of stroke. This chapter explains the systematic implementation of a working ML pipeline for analyzing the clinical workflow of risk factors that leads to stroke. Machine learning models in the broad category of parametric and non-parametric machine learning models are explained with illustrations. The maturity of deep convolutional neural nets in learning various classes of heartbeat is presented in detail. The ability of the deep learning concept of AI in CVD is discussed with a case study on the assessment of cardiac dynamics and detection of arrhythmia by classifying heartbeats.

The key importance of cardiovascular risk factor analysis lies in the exploratory data analysis of various social and biological factors in larger cohorts. Hence, this chapter aimed to the assessment of risk factors and their relationships in clinical trials. The foremost of this analysis is data cleaning and transformations that are necessary for clinical data to be amended in leveraging the AI technologies using the machine learning concept. The perpetual benefits of this approach are to understand the primary thoughts on how an individual's addiction to social factors influences sudden cardiac deaths. Also, the history of heart disease due to these addictions is assessed statistically. In event of this analysis, with due consideration to the social factor smoking status of an individual is found to be categorical viz, formerly smoked, never smoked, and smokes. However, a few unknown statuses are also noted in the dataset. These unknown facts are not null values, instead considered as not known. The number of individuals in a gender group of a cohort is considered for the impact on cardiovascular risk due to smoking status using histogram, bar, and pie plots.

The correlation metrics are estimated to identify the features that are more influenced by the risk of cardiovascular risks. Thus, EDA is more significant on its part in analyzing the risks due to smoking an individual. Further, the next feature considered for this analysis is work type. In this cohort study, individuals' works are of types children (non-working), government sectors, private sectors, and entrepreneurs. The residence types of these individuals are urban and rural. Hence, these social factors are the key features that help in evaluating the relationship between the gender groups and individuals as a whole. The distribution of stroke, heart disease, and hypertension among the cohorts is made known using quartile plots. These plots are more specific to the proportions say 25%, 50%, and 75% which are the 25^{th}, $50^{th,}$ and 75th percentile of the feature age in the cohort. The individuals in a cohort having hypertension are encoded as 1, and not having are encoded as 0. Similarly, individuals with a history of heart disease are encoded as 1, without a history of so are encoded as 0. Likewise, gender attribute in this cohort study is binary categorical and transformed as zero for males and zero for females. These binary variables are encoded as zeros and ones for transforming the datasets during pre-processing of the machine learning pipeline. Leveraging machine learning workflow for the diagnosis of sudden cardiac arrests and deaths lies in the quantification of relationships between the social factors like work type, residence type with biological factors like age, gender, average glucose level, body mass index (BMI), hypertension, history of heart disease, etc. The presence and absence of stroke in a dataset identify the individuals with a history of heart disease.

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Chapter 8
Designing Machine Learning-Based Variable-Order Bayesian Network in Predicting Sudden Cardiac Arrest and Death

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ABSTRACT

Recent surveys suggest that the majority of the world's population is unconcerned with their health. Aside from a hectic lifestyle, research reveals that stress is also a component in the development of many diseases. Sudden cardiac arrest and death (SCD) is a major public health concern that jeopardizes patient safety. As a result, detecting such illnesses only by ECG is difficult. The Bayesian Dirichlet equivalence score, AIC (akaike information criterion), and MDL (maximum description length) scores make up the variable-order Bayesian network (VOBN). On the basis of HRV (heart rate variability) acquired from ECG and using a hybrid classifier to identify SCD patients from normal patients, this study predicts sudden cardiac arrest before it occurs within 30 minutes. The validity of the suggested study is checked using the physionet database of cardiac patients and normal people, as well as the Cleveland dataset. The proposed method achieves 97.1% accuracy, 96.2% precision, 89.8% recall, 84.82% F1-score, 54.66% AUC, and 45.92% ROC, according to the results.

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INTRODUCTION

Heart failure (HF) has become a major public health issue in both Asia and the West, with an increasing prevalence. In Asia, the prevalence of heart failure ranges from 1.2 percent to 6.7 percent, depending on the population. HF with a low ejection fraction is a frequent disease with a bad prognosis. It's still difficult to accurately identify people with ischemic heart disease as well as idiopathic dilated cardiomyopathy who are at risk of SCD (sudden cardiac death). Current suggestions for ICD (implantable cardioverter-defibrillators) in these circumstances are nearly completely based on LVEF (left ventricular ejection fraction). This constraint is insufficient. Using myocardial deformation on echocardiography and MRI, noninvasive imaging has recently given insight into the process behind SCD (Kammoun et al., 2021). However, the function of these biomarkers in predicting arrhythmic mortality has not been studied in isolation.

The goal of this study is to see if biomarkers CT-proET-1, MR-proANP, and MR-proADM are linked to an elevated risk of arrhythmic death as well as all-cause mortality in HFrEF patients with ischemic and non-ischaemic dilated cardiomyopathy. Despite advancements in the survival rate of AMI (acute myocardial infarction), AMI-related OHCA (out-of-hospital cardiac arrest) remains a fatal condition. TIMI(Thrombolysis in myocardial infarction) evaluation is utilized to categorize coronary reperfusion following PCI (percutaneous coronary intervention), although it's uncertain if TIMI evaluation after emergent PCI is linked to short-term mortality in patients with AMI who had OHCA (Otaki et al., 2021).

SCD should be identified as the major endpoint whenever possible, even though determining the cause of death is not always straightforward. The so-called "grey zone fibrosis" mass, which is defined as the standard deviation from maximum signal intensity LGE, has recently been found to be more significantly related to SCD and VAs than LVEF (Zegard et al., 2021).

Figure 1. Generalized steps in machine learning
(Patel et al., 2020)

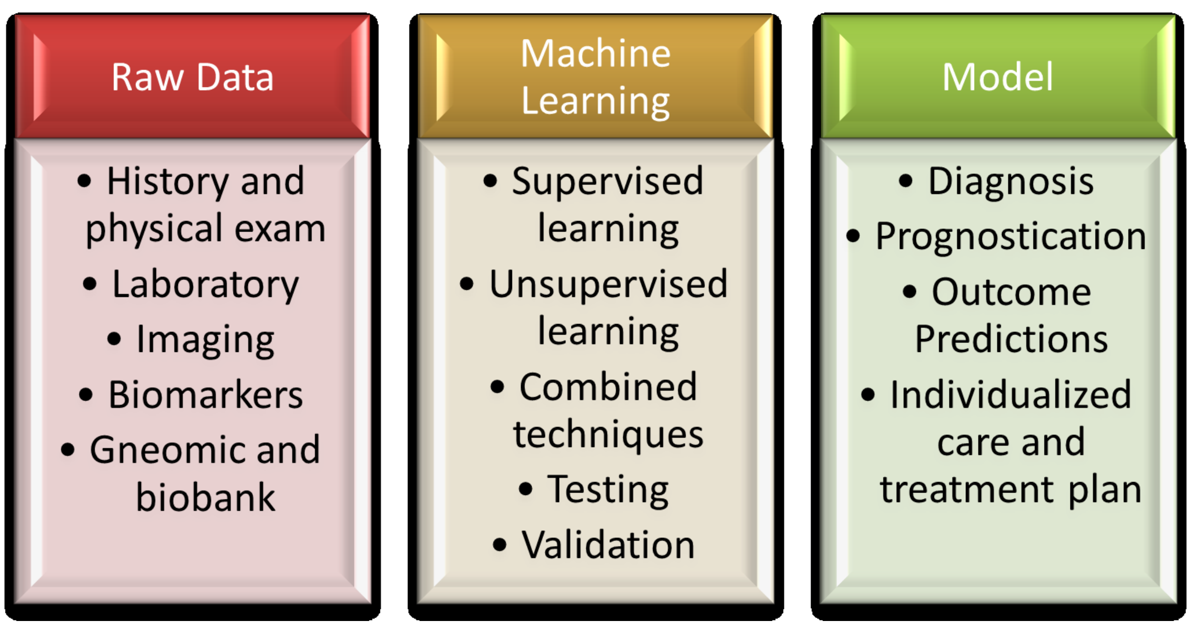


Figure 1 depicts steps involved in developing a predictive model utilizing machine learning which consists of raw data s input, machine learning process as processing unit, and model as output There are other machine learning algorithms available; however, logistic regression is the most basic type of machine learning method that we are familiar with. However, its inability to analyze data like a machine learning technique may limit its use in big data and difficult data analysis. There are 3 ML techniques such as supervised, unsupervised, and reinforcement learning.

The most common causes of arrhythmic SCD are ischemic heart disease and non-ischemic dilated cardiomyopathy. Antiarrhythmic medications' role is restricted to symptom alleviation, while ICD therapy is the only method that helps avoid SCD in high-risk individuals. Current guidelines propose choosing ICD candidates based on aetiology, heart failure symptoms, and a profoundly decreased LVEF, although these criteria are neither sensitive nor specific. The review looks at mechanisms of SCD in patients with ischemia or non-ischemic HF, as well as risk assessment and preventative measures in clinical practice (Corrado et al., 2020).

Several multivariate prognostic methods for chronic HF patients are proposed in the recent decade. These models, on the other hand, are ineffective at identifying ICD candidates with a high risk of SCD in HF patients with poor LVEF. The majority of the prognosis scores shown above were derived from trial databases and individuals included diverse kinds of heart failure. There is no specific research on the prognosis of people with poor LVEF. Moreover, despite the fact that all of the scores are "not parsimonious," some critical factors are left out of prognostic methods, such as medications, which are included in the I-PRESERVE, MAGGIC, and CC-HF.

Examine whether patients in our study waited too long to call 911. During the early pandemic period, the author found a sharp countrywide drop in hospital-treated acute coronary disease, possibly representing that fewer people are seeking care for cardiac symptoms (Solomon et al., 2020).

Bystanders may be hesitant to participate in community response to OHCA due to fears of spreading the disease. Additionally, EMS organizations have adopted additional screening of all 911 calls for suspected COVID-19 symptoms or known infection, as well as new systems for providing PPE to first responders to ensure their safety (Edelson et al., 2020).

The rest of this chapter is ordered as follows - Section II mentions a few existing research works, Section III shows the proposed approach and methodologies, Section IV exhibits experimental outcomes and discussion, and, finally, Section V ends up with a conclusion and future work.

RELATED WORKS

During an arrhythmic event patient's life was failed to save which contains appropriate ICD therapy without using ventricular tachycardia acceleration which results in arrhythmic death in patients who already had installed ICDs. Resuscitated cardiac arrest was defined as ventricular fibrillation or ventricular tachycardia >240 bpm leading to syncope before ICD therapy, as well as numerous slower ventricular tachycardia events leading to syncope as well as ICD discharge without ICD therapy-related acceleration as well as other ICD, discharges due to ventricular tachycardia (Burger AL et al., 2020), (Pezawas T et al., (2020).

Ventricular tachyarrhythmias are common in patients with heart failure and a low left ventricular ejection percentage (HFrEF). A total of 160 HF patients with ischemic or non-ischaemic DCM (dilated cardiomyopathy) as well as 30 healthy controls were included in this potential observational study. ArD(Arrhythmic death) or resuscitated CA was the primary outcome (resCA).CT-ET1, MR-proANP, and MR-proADM levels were all higher in HFrEF patients. In patients with ICM, plasma levels of MR-proANP can be used to predict arrhythmic mortality (Burger AL et al., 2021).

In individuals who have suffered from OHCA, enhancing survival to hospital release is critical since long-term prognosis can be relatively favorable if proper treatment is given early on. Regardless of original ECG results or patient age, CAG with or without PCI improves neurological results in individuals who have experienced OHCA (Kim KH et al., 2020).

In individuals with coronary artery disease without acute systolic dysfunction as well as HF with intact ejection fraction, SCD is the major cause of cardiovascular mortality. While the risk of SCD is lower in patients with an LVEF of more than 35%, the absolute number of SCDs is higher in those with a substantially diminished LVEF. Despite these findings and a vast amount of data available, there are no clear recommendations for lowering the risk of SCD in people with a mid-range or maintained LVEF. Continuous advances in risk assessment based on electrophysiological as well as imaging methods indicate a more precise determination of patients who would acquire an advantage from implantation of ICD, which remains an unmet requirement in this population of patients (Pannone et al., 2021).

To predict cardiac arrest, traditional statistical methods have been tried. They've frequently looked at group-level differences with a small number of factors. On the other hand, the ML method, which is part of a developing trend in predictive medical analysis, has yielded outstanding outcomes by providing individualized predictive assessments on more complicated data. "Valsartan in Acute Myocardial Infarction" (VALIANT) experiment, which included 14,703 patients with symptomatic CHF or a minimized ejection fraction of 40% within ten days of severe MI, gives some insight into the time of death from myocardial rupture later after MI (Al Azwari, S. 2021).ML is being used to improve the accuracy of myocardial rupture prediction following a heart attack.

The goal of our research (Jayaweera et al., 2020) is to use Reinforcement Learning (RL) to anticipate the prospect of cardiac arrests as well as the presence of stress in real-time utilizing a wearable device prototype. This used RF, KNN, and LR classification methods to train three models that correctly predicted abrupt cardiac arrests with accuracies of 99.93%, 99.10%, and 94.47%, respectively.

Also used the same techniques to train three more models to predict stress, with accuracies of 99.87 percent, 96.83 percent, and 65.00 percent, respectively. As a result of the findings of this study, an integrated structure adept at predicting various health-related diseases using sensor data acquired from wearable sensors is possible. People's lives are in jeopardy (Maashi MS et al., 2020).

Between 2008 and 2012, data from the American College of Surgeons' National Surgical Quality Improvement Program was used in a retrospective cohort analysis. Incidence and risk factors for intra-operative, postoperative CPR, as well as 30-day mortality, were studied using Firth's penalized logistic regression. To anticipate observed outcomes, a basic prediction model was built and internally tested. In surgical patients, the number of cardiac arrests that need CPR has reduced over time. Intraoperative CPR, postoperative CPR, and perioperative mortality risk variables have all been exhausted. To determine patients at high risk, a simplified strategy based on a five-factor model was presented. Cardiac arrest needs CPR which is associated with a considerably greater fatality rate postoperatively than intraoperatively (Kaiser HA et al., 2020).

In patients at high risk for ventricular arrhythmias, most clinical trials are demonstrated that ICD therapy offers a significant mortality advantage. This has been demonstrated in both primary and secondary prevention trials, such as the AVID (Antiarrhythmic Versus Implantable Defibrillators) study, which looked at patients who had survived a near-fatal ventricular arrhythmia.LV ejection fraction of S 35 percent was found to be the only patient feature. In patients with dyssynchronous LV contraction associated with dilated cardiomyopathy, cardiac resynchronization therapy has been shown to enhance mortality (Chai Y et al., 2021).

Variations in blood pressure, sugar, pulse rate, and other factors can result in cardiovascular illnesses such as restricted or blocked blood arteries.HF, aneurysms, peripheral artery disease, heart attacks, strokes, and even SCA can all be caused by it. Many types of heart disease can be detected or diagnosed using various medical tests when the family medical history and other factors are taken into account. However, predicting heart disease without any medical tests is extremely challenging. Goal of this initiative is to diagnose various cardiac illnesses and take all necessary actions to prevent them at a reasonable charge as early as feasible. For the prediction of cardiac disorders, we use the 'Data mining' methods, in which attributes are input into SVM, RF, KNN, and ANN classification techniques. Preliminary readings and studies acquired with this technology are used to determine the likelihood of discovering cardiac illnesses at an early stage when they can be entirely treated with the proper diagnosis.

The ECG risk score was successful in finding patients with a high SCD risk in the general population. Combining ECG risk factors could help with SCD risk categorization (Holkeri A et al., 2020). Weng et al., (2022) applied PCA to a dataset of commonly known cardiac-disease risk features on a minority population of Punjabi Indians across three generations. Thedataset included features such as weight, waist circumference, body mass index, blood pressure, and pulse rate. In Fitriyani et al., (2022) the author used feature selection with a Chi-squared feature evaluator in conjunction with the random forest ML algorithm to build a model for cardiac-disease prediction on the stat log cardiac-disease dataset

The goal of this study was to see how the COVID-19 pandemic could affect OHCA response and outcomes in two US towns with low infection rates. From March to May 2020, the community's response to OHCA changed, with fewer bystander CPRs, longer EMS response times, and worse OHCA survival rates. These findings underscore the pandemic's indirect deleterious influence on OHCA, even in communities with low COVID-19 prevalence, and lead to potential mitigation strategies (Uy-EvanadoA et al., 2021).

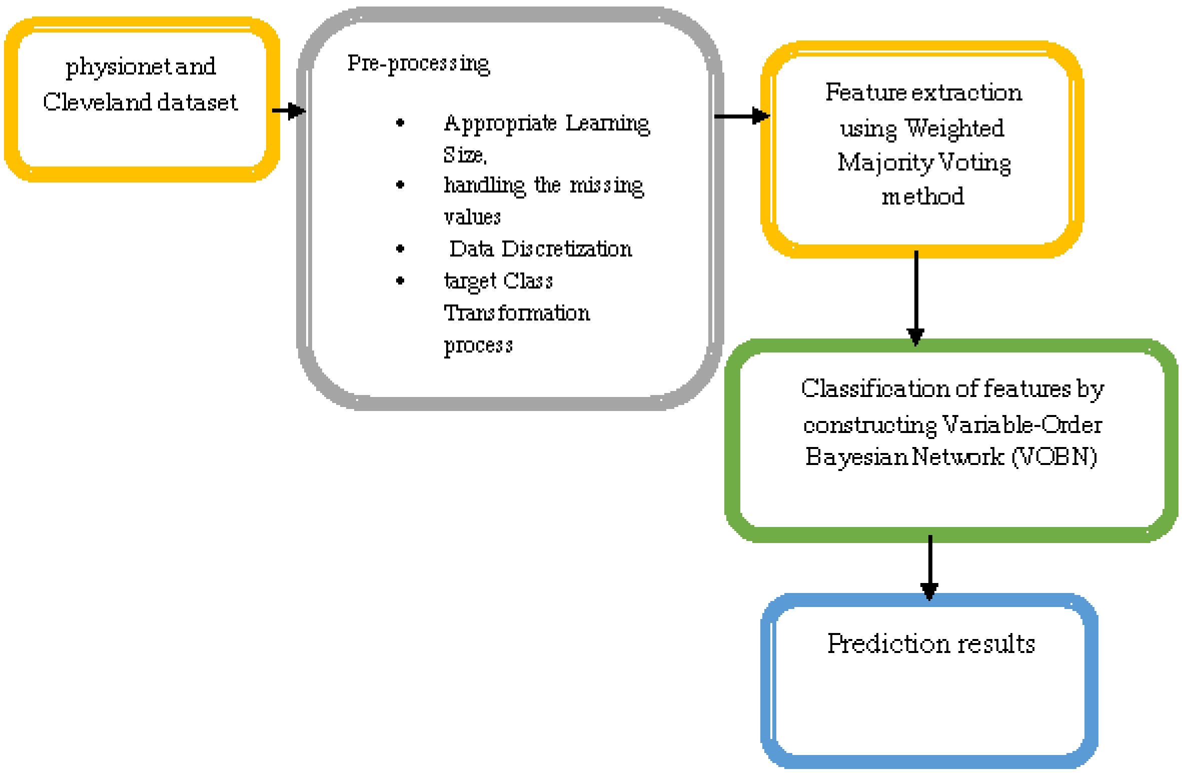
To find existing CA as well as SCD registries, as well as their global coverage and data collection, and validation techniques. Many CA registries exist around the world, but their population coverage is uneven. Surveillance from many sources and the number of SCD registries is decreasing, and designing and maintaining them is becoming increasingly difficult. Maximizing case identification and case verification have been noted as challenges (Paratz ED et al., 2020).

From the above methods, it is found that SCD has high mortality and its early prediction is a challenge for the medical community. Patients with congestive heart failure are more vulnerable to SCD. Ability to accurately predict SCD is key to saving patients' lives and reducing the mortality rate which is not possible by basic classification methods. So, it is significant to design and solve a specific problem by developing an intelligent system without being categorically programmed for it. The learning of the program is done by deriving knowledge from a large amount of data which is useful in making predictions.

SYSTEM MODEL

In this section, a proposed methodology is introduced for feature extraction and classification of sudden cardiac arrest and death prediction at each stage. Initially, the datasets such as physionet and Cleveland datasets are adopted for the cardiac attack. These are given to pre-processing step, where Appropriate Learning Size, handling of the missing values, Data Discretization, target Class Transformation process can be performed at this stage. In the second step, the feature extraction is done using the Weighted Majority Voting method. Finally, the extracted features are classified using Variable-order Bayesian network (VOBN). The diagrammatic representation illustration of the suggested methodology is shown in figure-2. A detailed description of every technique used in each phase is briefly explained in the below sections.

Figure 2. Block diagram for proposed sudden cardiac arrest and death prediction method



Dataset Description

This research uses the two datasets such as the Cleveland dataset and the physioNet heart disease dataset from UCI ML (machine learning) repository. Cleveland dataset consists of 303 samples with 14 attributes. To encourage the study and stimulate development in this vital area of electrophysiology, PhysioNet has launched an SCD Database. The MIT-BIH Malignant Ventricular Arrhythmia Database began with 23 complete Holter recordings, from which half-hour extracts have been provided to researchers since 1989. There are now 18 individuals with underlying sinus rhythm in the database, one who was constantly paced, and four who have atrial fibrillation. All of the patients experienced a persistent ventricular tachyarrhythmia, with the majority of them experiencing cardiac arrest. The Cleveland dataset is explained in Table 1.

Table 1. Dataset description

Attribute	Description	Domain of Values
Sex	Sex	0_Female, 1_Male
Age	Age in years	29-79
Cp	Chest pain type	1_Typical angina, 2_Atypical
Chol	Serum cholesterol	126 to 564 mg dL
Trestbps	Resting blood sugar	94 to 200 mm Hg
Fbs	Fasting blood sugar >120 mg dL	0_ False, 1_True
Thalach	High heart rate attained	71 to 202
Restecg	Resting ECG result	0_Normal, 1_ST-T wave abnormality2_LV hypertrophy
Exang	Exercise tempted angina	0_No, 1_Yes
Slope	Slope of peak exercise ST segment	1_Upsloping, 2_Flat, 3_Downsloping
Oldpeak	ST depression tempted by exercise based on rest	0 to 6.2
Ca	Number of major vessels colored by fluoroscopy	0-3
Target	HD	0-4
Thal	Defect type	3_Normal, 6_Fixed defect, 7_Reversible

ECG signals acquired from MIT-BIH physionet database. It contains a variety of ECG data sets for various disorders.NSR database and the SCD database were chosen for investigation. Twenty patient signals were chosen from each of the above datasets, for a total of 40 signals. Every patient has more than 1hr ECG recording in the database, of which 30 minutes of ECG data shortly before a cardiac arrest is used in this study. Because a 5-minute ECG signal is adequate for extracting HRV features, an overlapping window of 10 minutes was used in this study. As a result, five to ten-minute signals are obtained for each patient. Thus, a total of 200 signals are obtained, with 100 normal and 100 cardiac arrest signals. The first group was utilized for analysis or training, while the second was utilized for testing. For the training phase, 150 signals are considered, and for the testing stage, 50 signals are considered.

SDDB was used to identify 20 patients with VF. Their VF onset positions were then determined using their associated ECGs.ECG samples of one-hour length were extracted right before the VF onsets. Similarly, ECGs of another 20 individuals were chosen at random from the NSRDB. Random placements were used to extract one-hour ECG segments. From both databases, a total of 40 ECG segments were recovered. Finally, RRIs were evaluated to create the RRI array of 1hr length. The RRI was calculated using the dataset's annotated R peaks. RRI array was then subjected to a 5-minute overlapping sampling window.HRV indices were determined for every of these 5-minute RRI arrays. A total of 72,000 records were produced as a result. Using the parent dataset's annotations, each record was then labeled according to whether or not a person received an SCA within one hour. For both classes, the resultant dataset contained 36,000 records. Finally, the SCA prediction model was trained using the generated dataset.

Pre-Processing of Data

As input for local learning, every local learner will gain a global data slice of N/K rows. First stage in Adaptive 2-Stage Data Slicing is to execute global data slicing on a large dataset with N records as well as K local learners to distribute data equitably across obtainable local learners for load balancing as well as subsequent learning. E local learner will get Nd data slices for dispersed learning, with every data slice having a size of ALS. Nd evaluated by Eqn (1):

$$\mathrm{Nd} = \frac{N}{K * ALS} \tag{1}$$

Handling Missing Values- Here are five methods for dealing with lost data:

1. Deleting Rows
2. Replacing with mean/median/mode
3. Allot a unique category
4. Forecast missing values
5. Using techniques that support missing values. Because there are a few missing values in this article, it was decided to delete rows.

Transformation of the Target Class- target class consists of values (0, 1, 2, 3, 4).Where 0 indicates health (no cardiac disease) and (1, 2, 3, 4) indicates the existence of different degrees of illness. The lack or presence of cardiac disease is of interest, hence the class must be kept small (0, 1). The first, second, third, and fourth levels were all converted to one.

Data Discretization-Five of the 14 characteristics in our dataset is continuous. Because the variables in variable-order Bayesian network (VOBN) models are discrete, we must categorize this continuous data. To discretize data, we rely on expert knowledge. Age, trestsbp, chol, thalach, and old peak are continuous qualities.

Feature Extraction using the Weighted Majority Voting Method

The further computations are then performed on pre-processed data by the feature extractor training module. It is needed to combine independently trained classifiers of every group into appropriate combination techniques. The ensemble mechanism of Weighted Majority Voting (WMV) sorts an unlabeled instance into a class based on the most common votes or highest number of votes. Plurality Vote (PV) approach is the name given to the WMV ensemble technique. The WMV mechanism is frequently used to compare the performance of different models. Mathematically it is given by equation (2),

$$\mathrm{class}(\mathrm{x}) = \mathrm{arg}\, max_{c_i \in dom(y)} \left(\sum_k g\left(y_k(x), c_i \right) \right) \tag{2}$$

Where the feature of the Kth extractor is denoted as $y_k(x)$ and $g(y,c)$ represents about index function which can demonstrate as follows in (3)

$$g(y,c) = \begin{cases} 1 & y = c \\ 0 & y \neq c \end{cases} \tag{3}$$

If the probabilistic method is used, crisp extraction $y_k(x)$ is got from the following equations (4)

$$\text{class}\left(\text{x}\right) = \arg max_{c_i \in dom(y)} PM_k\left(y = c_i \mid x\right) \tag{4}$$

Where $PM_k(y=c_i|x)$ denotes the probability of class c for an instance x, and is used to show the extractor M_k. For each base classifier, each voting procedure provides a distinct weight. The classifier's accuracy in predicting this learner's severity level determines this weight.Correspondence function argmax($wTm\alpha(x)$ + bm) provides higher decision value to class.Each of the n base classifiers predicts a severity category for each bug report. To set margin as well as to enhance margin, given as follows.

$$\Omega i = (W.Xj+b)yj \tag{5}$$

Where, $\Omega = \dfrac{1}{\sqrt{w}}$

$Xj = xj' + \mu \dfrac{w}{\sqrt{w}}$

$$W = 1(\text{default}) \tag{6}$$

To enhance margin for linearly separable cases as in equation (7),

$$mx\ (W.Xj+b)yj>\Omega \tag{7}$$

The above explained is general for margin setup. After the features are extracted, there must be a proper perspective to properties as well as a CSV file produced according to the values of properties.

Algorithm
Input-
Learning cost = Π
Π= {j=1,2,....m}
M=iterations
Initialize A(u) and B(u)
Output-
X<- predicted result
Start
Training and testing data<-D(x)
Fixing the attributes (a,b)
If
Calculate the entorpy (z)
Z<-(x,y)
Calculate the probability and fix the classes (S)
S=S1,s2,s3....sn

Check S<Z
End if
Compute the slacking method and finalize (F)
Fi< m
if
Fi=data_slack
Neglect the process
Else
Repeat the slacking
Pick the minimum parameter (J)
J¬x
End the process

Construction of Variable-Order Bayesian Network (VOBN)

Forward Operation

Next, enter {X, T} learning samples, where X is the learning samples' input vector and T is the corresponding output vector:

$X=(x_1,x_2,\ldots,x_k,\ldots,x_n)$, 1£k£n (8)

$T=(T_1,T_2,\ldots,T_m,\ldots,T_q)$, 1£m£q (9)

N is several input layer nodes; q is several output layer nodes. Forward data propagates through the input layer and hidden layer to the output layer. The created weight value is the learning outcome of the classification of performance patterns. They primarily contain the following measures.

Step 1: Nodes value in the hidden layer is

$$i_{1j} = \sum_{k=1}^{n} w_{1kj} x_k , 1 \le j \le p \tag{10}$$

$$h_j = f(i_{1j} + \theta 1_{j}) \tag{11}$$

Where the threshold of node j is $\theta 1_j$. The sigmoid function given by Rumelhart is the activation function f used:

$$f\left(i_{1j}\right) = \frac{1}{1+e^{-i_{1j}}} \tag{12}$$

Step 2: (Calculating output value of output layer nodes). Input values for output layer nodes m are

$$i_{2m} = \sum_{j=1}^{p} w_{2jm} h_j, 1 \le m \le j \tag{13}$$

Node m output value is

$$O_m = f(i_{2m} + \theta 2_{m)} \tag{14}$$

Where $\theta 2_m$ output layer node threshold m and f is is activation function specified by the sorting process

Back Operation

Evaluate output value error and predicted output layer value error. From the output layer, a backpropagation error via hidden in the input layer. Values of connection weight are adjusted. The steps are as follows.

Step 1: Error between O_m learning value of output layer m node and the output value of T_m learning samples is

$$\varepsilon \mathrm{m} = |\mathrm{O}m - Tm_{|} \tag{15}$$

Step 2: (learning error testing). $\varepsilon 0$ is high learning error, which is set by the user in [0,1] interval.

When $\max(\mathring{a}_{\mathrm{m}}) \le \mathring{a}_0$, enter the next learning sample. Network weights are adjusted and original learning samples are reentered. When all learning samples fulfill the above criteria, the learning process is terminated.

Step 3: (evaluate learning error in output layer nodes). Nodes output layer m, learning error is

$$d_{2m} = O_m(1 - O_m)\,(O_m - T_m) \tag{16}$$

Step 4: Hidden layer j learning error is

$$d_{1j} = h_j \left(1 - h_j\right) \sum_{m=1}^{q} w_{2jm} d_{2m} \tag{17}$$

Step 5 (revise the value of the connection weights matrix w_2). Set weight value as modified current weight value at time t+1; then set new weight value.

$$w_{2jm}\left(t+1\right)=w_{2jm}\left(t\right)+\eta d_{2m}h_j+\alpha\left[w_{2jm}\left(t\right)-w_{2jm}\left(t-1\right)\right] \tag{18}$$

where the learning rate is η and the momentum factor is α. In scope [0,1], both α and η exists. Using alpha will speed up learning speed and help to solve the common BP algorithm's local minimum problem.

Step 6: (revise the value of the connection weight matrix w_2). Consider,

$$w_{1kj}\left(t+1\right)=w_{1kj}\left(t\right)+\eta d_{1j}x_k+\alpha\left[w_{1kj}\left(t\right)-w_{1kj}\left(t-1\right)\right] \tag{19}$$

Step 7: (revise the threshold $\theta 2_)$. Output node layer threshold is

$$\theta_{2m}\left(t+1\right)=\theta_{2m}\left(t\right)+\eta d_{2m}h_j+\alpha\left[w_{2jm}\left(t\right)-w_{2jm}\left(t-1\right)\right] \tag{20}$$

Step 8: (revise the threshold $\theta 1_)$. The hidden layer threshold layer is

$$\theta_{1j}\left(t+1\right)=\theta_{1j}\left(t\right)+\eta d_{1j}+\alpha\left[\theta_{1j}\left(t\right)-\theta_{1j}\left(t-1\right)\right] \tag{21}$$

Let αi, i = 1…N represent the characteristics or weights of clusters which are defined below. Then the property i exists for datum α whenα€ αi

The error at classification is as indicated in equation (22):

$$\int \alpha-\beta i \tag{22}$$

Then, for the network, global error E of classification is defined as in equation (23)

$$\text{E} = \frac{1}{n}\sum_{i=1}^{n}\int \alpha-\beta i . f\left(\alpha\right)d\alpha \tag{23}$$

Where, $f(\alpha)$ represents the density of the probability distribution for the data given as input

Let I = I1, . . . …, IN be the optimal partition when E is minimum. Then αi denote the values by which E is minimized. The procedure used to determine the sets Ii and its related weights Ii are given in simple terms. Consider x(1), . . ., x(P) as a series of random values obtained from the dataset, which is distributed with f (x) being the density and initial weight values β1(0), . . ., βN (0) are taken at random. An input pattern x(n) where n ranges from 1 to P, compute every difference x(n)−βi (n −1)| and the neuron j having minimum difference |α(n) − βj (n − 1)| is said to be the winner neuron. To change the weight of this neuron, the below-defined way is used or in a few cases, changes are made in the weights of the adjacent neuron. This process is iterative using another pattern x(n + 1) and new weights βi (n) till the terminating criteria are satisfied. Actually, by approximating, this algorithm is considered as a gradient approach used in the function E which is indicated in equation (24):

$$\text{Bi(n+1)} = \beta\text{i(n)}+\Omega\text{(n)}[\alpha\text{(n)}-\beta\text{i(n)}]-\frac{1}{2}\ \Omega\text{(n).E} \tag{24}$$

The data gathered was utilized to build VOBNs for determining post-stroke outcomes. For each instance of patient data, extracted a total of 76 random variables.VOBN is a focused acyclic graph in which the nodes indicate random variables and the links reflect node dependencies.

$$p\left(v\right)=\prod_{v_i \in v} P\left(V_i \pi\left(Vi\right)\right) \tag{25}$$

where $\pi(\mathrm{V}i)$ is a set of parent nodes of Vi. Learning algorithm now evaluates how well signified distribution describes given data set by measuring and comparing the quality of VOBNs.The log-likelihood is a typical metric for assessing the quality of a VOBN, as seen below.

$$LL\left(B \overset{\Delta}{\rightarrow} D\right)=\sum_{v_i}\log(P(V_i\left(\pi B\left(V_i\right)\right)) \tag{26}$$

Where, $B \overset{\Delta}{\rightarrow} D$ is VOBN over D and $\pi\mathrm{B}(\mathrm{V}i_{)}$ is parent nodes of Vi

Various ways of measuring quality have been investigated. Based on the Bayesian Dirichlet equivalence score, AIC, and the MDL, the algorithm found the optimal VOBN. MDL score is used to calculate the quality of a VOBN. MDL score is defined as

$$MDL=-LL\left(B \overset{\Delta}{\rightarrow} D\right)+{}^{logN}\!/_{2} \tag{27}$$

where |B| is a number of parameters in B and N is a number of occurrences in D. Better the network, the lower the MDL score.For the type of VOBN structure, constructed TAN (tree-augmented network) represents the limit number of parents to 2 nodes.

Prediction Method

The data preparation method filtered records with missing outcome variables as well as the exclusion method, yielding a total of 76 features. This used two alternative feature selection algorithms.

The process of limiting the number of random variables under consideration by generating a set of principal variables is known as feature selection or dimension reduction. Feature selection reduces the problem of overfitting, which is due to irrelevant or redundant variables that can heavily skew the classifier's performance. These approaches are applied to the data set before the training learning method or are used to incorporate feature selection in the learning process. Feature selection methods are divided into filters, wrappers, or embedded techniques in many studies. Regardless of the data modeling method used, filter techniques select features based on a performance metric. By rating variables or finding a subset of variables, the filter strategy chooses random variables based on data gain score, ReliefF, or a correlation-based technique. Wrapper approaches, unlike filter methods, assess the utility of a subset of characteristics by training a model on it. Performance of VOBNs was tested using a minimum variable set designated by data gain and VOBN techniques, which are commonly used in filter and wrapper approaches. First, put the VOBN classifier to the test with features picked by data gain based on each feature's entropy.Other feature selection technique, which considers VOBN classifier characteristics, minimizes the variable set by calculating VOBN classifier's performance in cross-validation, in which a search method selects a subset of attributes to optimize AUC in prediction. Goal of AUC optimization is to balance the number of survivors and mortal individuals. System built a VOBN prediction model utilizing reduced variables from feature selection to find optimal VOBN structures and parameters. This used a variety of methods to assess the performance of prediction algorithms (1) a basic TA-VOBN, (2) TA-VOBN with data gain-filtered features, and a tree-augmented VOBN with VOBN wrapper-filtered features. AUC, specificity, and sensitivity of 10-fold cross-validations were used to assess the performance of all VOBNs and predictive models.

Performance Analysis

The experimental result is using the parameters such as accuracy, precision, recall, F1-score, AUC, and ROC. These parameters are compared with three states of art techniques such as CART (Classification and Regression Tree), SVM(Support Vector Machine), and Reinforcement Learning (RL) with the proposed variable-order Bayesian network (VOBN).

CART (Classification and Regression Tree)- In the decision tree, the nodes are split into subnodes based on a threshold value of an attribute. The CART algorithm does that by searching for the best homogeneity for the subnodes, with the help of the Gini Index criterion. The root node is taken as the training set and is split into two by considering the best attribute and threshold value. Further, the subsets are also split using the same logic. This continues till the last pure sub-set is found in the tree or the maximum number of leaves possible in that growing tree. This is also known as Tree Pruning. The limitation is, a small change in the dataset can make the tree structure unstable which can cause variance

Support Vector Machine- (SVM) is a supervised machine learning algorithm that can be used for both classification and regression challenges. However, it is mostly used in classification problems. In the SVM algorithm, we plot each data item as a point in n-dimensional space (where n is a number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the two classes very well. The limitation is, that the SVM algorithm is not suitable for large data sets. SVM does not perform very well when the data set has more noise i.e. target classes are overlapping. In cases where the number of features for each data point exceeds the number of training data samples, the SVM will underperform.

Reinforcement Learning is a feedback-based Machine learning technique in which an agent learns to behave in an environment by performing the actions and seeing the results of actions. For each good action, the agent gets positive feedback, and for each bad action, the agent gets negative feedback or a penalty. The limitation is, that this algorithm is not preferable for solving simple problems. This algorithm needs a lot of data and a lot of computation

Accuracy presents the ability of the overall prediction produced by the model. True positive (TP) and true negative (TN) provide the capability of predicting the absence and presence of disease. False-positive (FP) and false-negative (FN) present false predictions made by the used model. The formula for accuracy is given as in equation (28):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{28}$$

Table 2 shows a comparison of accuracy between existing CART, SVM, RL methods, and the proposed VOBN method.

Table 2. Comparison for accuracy

Number of datasets	CART	SVM	RL	VOBN(proposed)
100	93.7	94.1	95.7	96.2
200	93.8	94.5	95.9	96.5
300	94.1	94.9	96.2	97.3
400	94.5	95.0	96.5	97.5
500	94.8	95.2	96.9	98

Figure 3. Comparison of accuracy

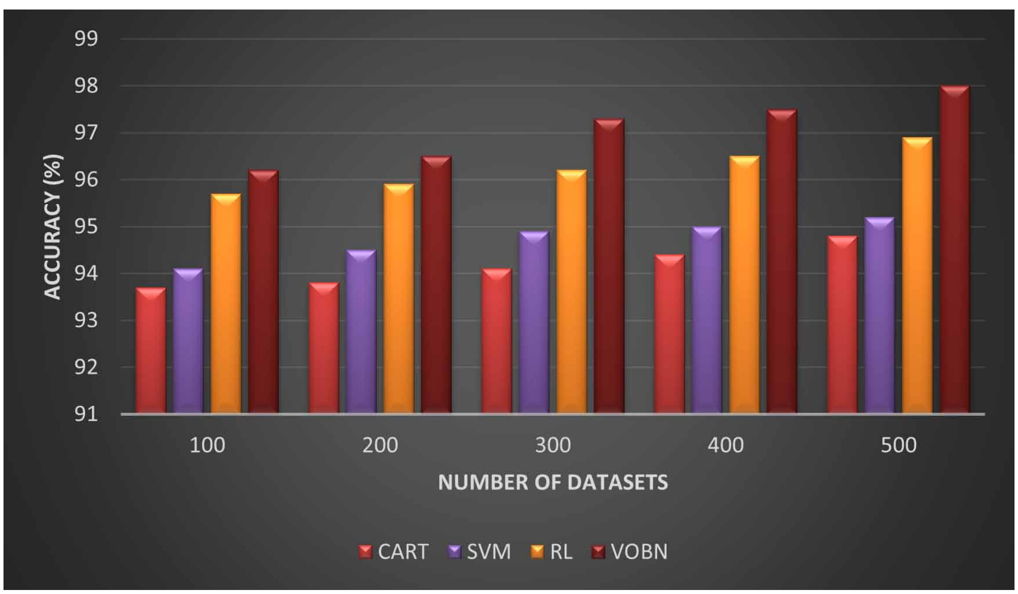


Figure 3represents a comparison of accuracy between existing CART, SVM, and RL methods and the proposed VOBN method where the X-axis indicates a number of datasets and the y-axis represent percentage accuracy. The orange-red color indicates CART, violate color indicates SVM, the light green color indicates RL, and the teal color indicates the proposed VOBN technique. When compared, existing CART (Classification and Regression Tree), SVM(Support Vector Machine), Reinforcement Learning (RL) methods achieve 94.18%, 94.74%and 96.24%while the proposed variable-order Bayesian network

(VOBN) method achieves 97.1%which is 3.08% better than CART,3.64% better than SVM, and 1.14% better than RL.

- **Precision** measure the success of the disease classification model, respectively. Precision refers to a classifier's ability to correctly predict a positive result when the disease is present. It is computed as indicated in equation (29):

$$Precision\left(P\right)=\frac{TP}{TP+FP} \tag{29}$$

Table 3 represents a comparison of precision between existing CART, SVM, and RL methods, and the proposed VOBN method.

Table 3. Comparison for precision

Number of datasets	CART	SVM	RL	VOBN(proposed)
100	92.2	93.1	94.3	95.7
200	92.6	93.4	94.5	95.8
300	93.1	94.1	94.8	96.2
400	93.4	94.4	95.2	96.5
500	93.8	94.6	95.4	96.8

Figure 4. Comparison of precision

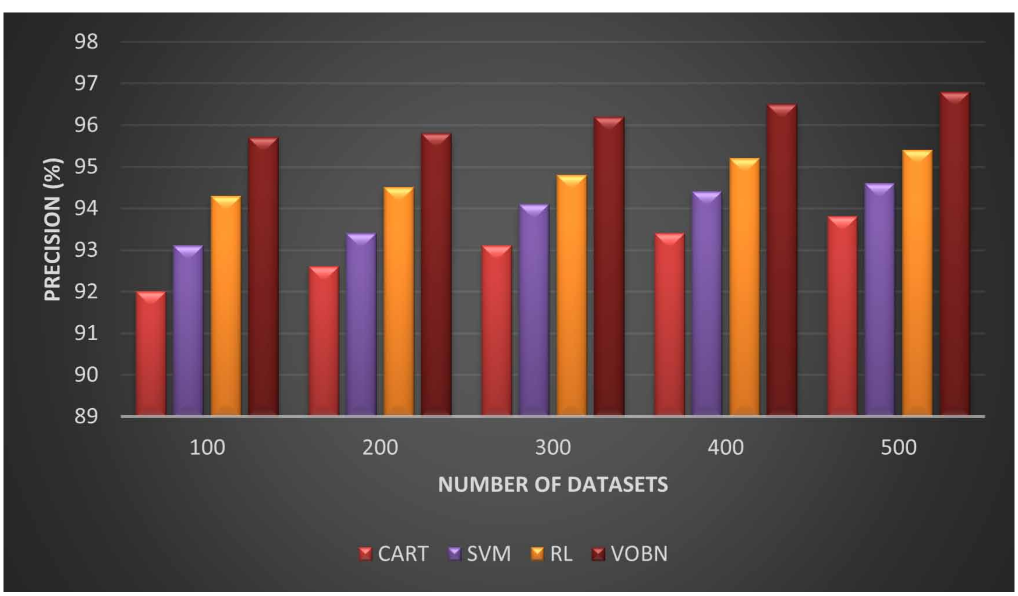


Figure 4represents a comparison of precision between CART, SVM, and RL methods and the proposed VOBN method where the X-axis indicates a number of datasets and the y-axis represent precision in percentage. The orange-red color indicates CART, violate color indicates SVM, the light green color indicates RL, and the teal color indicates the proposed VOBN technique. When compared, existing CART (Classification and Regression Tree), SVM(Support Vector Machine), Reinforcement Learning (RL) methods achieve 94.18%, 94.74%and 96.24%while the proposed variable-order Bayesian network (VOBN) method achieves 96.2%which is 3.22% better than CART,3.72% better than SVM and 2.44% better than RL.

The recall is the likelihood of a classifier predicting a negative result when no sickness is present. It is computed as indicated in equation (30):

$$Recall\left(R\right)=\frac{TP}{TP+FN} \tag{30}$$

Table-4 represents a comparison of recall between existing CART, SVM, RL methods, and the proposed VOBN method.

Table 4. Comparison for recall

Number of datasets	CART	SVM	RL	VOBN(proposed)
100	84.4	86.1	87.9	89.2
200	84.8	86.4	88.1	89.4
300	85.4	86.9	88.6	89.8
400	85.7	87.1	89.2	90.1
500	85.9	87.5	89.5	90.5

Figure 5. Comparison of recall

Figure 5shows a comparison of recall between existing CART, SVM, and RL methods and the proposed VOBN method where the X-axis shows a number of datasets and the y-axis represents recall in percentage. The orange-red color indicates CART, violate color indicates SVM, the light green color indicates RL, and the teal color indicates the proposed VOBN technique. When compared, existing CART (Classification and Regression Tree), SVM (Support Vector Machine), Reinforcement Learning (RL) methods achieve 85.24%, 86.8%and 88.66%while the proposed variable-order Bayesian network (VOBN) method achieves 89.8%which is 4.44% better than CART,3% better than SVM and 1.72% better than RL.

F1- Score is used to determine the accuracy of the forecast. It's viewed as precision and recall's weighted average (or harmonic mean). A score of 1 is regarded as the best, while a score of 0 is considered the worst. TNs aren't taken into account. As seen in equation (31), the F1-Score can be calculated:

$$F1-Score = \frac{2*P*R}{P+R} \tag{31}$$

Table-5 represents a comparison of F1-Score between existing CART, SVM, and RL methods, and the proposed VOBN method.

Table 5. Comparison for F1-Score

Number of datasets	CART	SVM	RL	VOBN(proposed)
100	79	81.1	82.5	84.2
200	79.1	81.3	82.9	84.5
300	79.5	81.5	83.1	84.9
400	80.4	82.5	83.4	85.1
500	80.6	82.7	83.6	85.4

Figure 6. Comparison of F1-Score

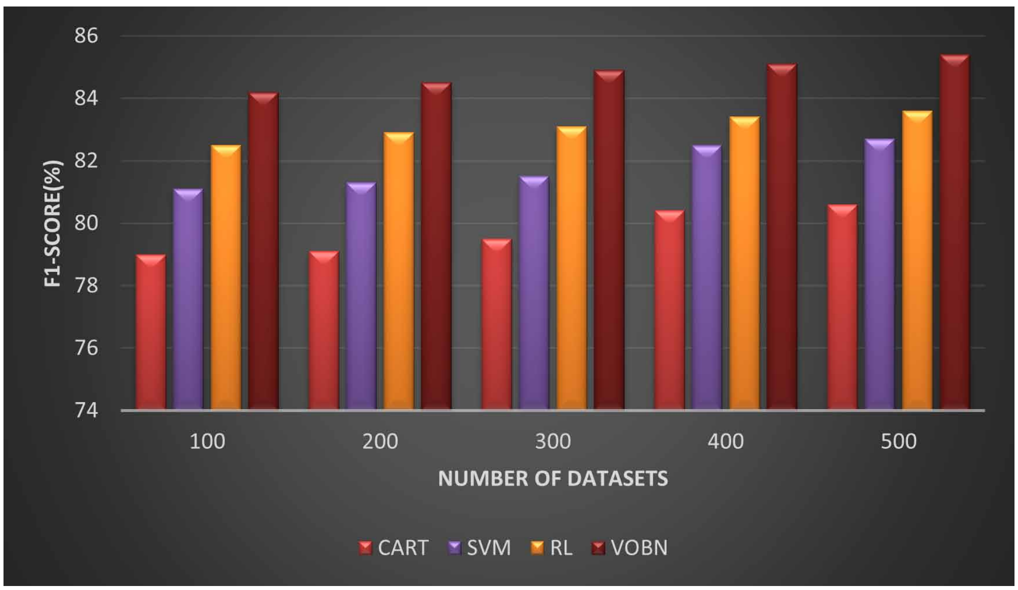


Figure 6 shows a comparison of the F1-Score between CART, SVM, and RL methods, and the proposed VOBN method where the the X-axis indicates a number of datasets and y-axis represents the F1-Score in percentage. Orange-red color indicates CART, violate color indicates SVM, light green color indicates RL, and teal color indicates the proposed VOBN technique. When compared, existing CART (Classification and Regression Tree), SVM(Support Vector Machine), Reinforcement Learning (RL) methods achieve 79.72%, 81.82%and 83.1%while the proposed variable-order Bayesian network (VOBN) method achieves 84.82%which is 5.1% better than CART,3% better than SVM and 1.72% better than RL.

ROC curve shows the trade-off between *TPR* and *FPR*, where *TPR* and *FPR* are described as given in equations (32) and (33):

$$TPR = \frac{TP}{TP + FN} \quad (32)$$

$$TFR = \frac{FP}{FP + TN} \quad (33)$$

The model is better if the ROC curve is closer to the upper left corner of the graph. AUC stands for the area beneath the curve. The model is better when the area is closer to 1. In medical data, place a higher value on recall than accuracy. The higher the recall rate, the less likely it is that a patient with a lung disease risk will be expected to have no lung disease risk.

Table-6.shows a comparison of AUC between existing CART, SVM, and RL methods, and the proposed VOBN method.

Table 6. Comparison for AUC

Number of datasets	CART	SVM	RL	VOBN(proposed)
100	50.1	49.9	52.4	53.9
200	50.4	51.1	52.7	54.1
300	50.6	51.4	52.9	54.6
400	51.1	51.9	53.1	55.1
500	51.3	52.1	53.6	55.6

Figure 7. Comparison of AUC

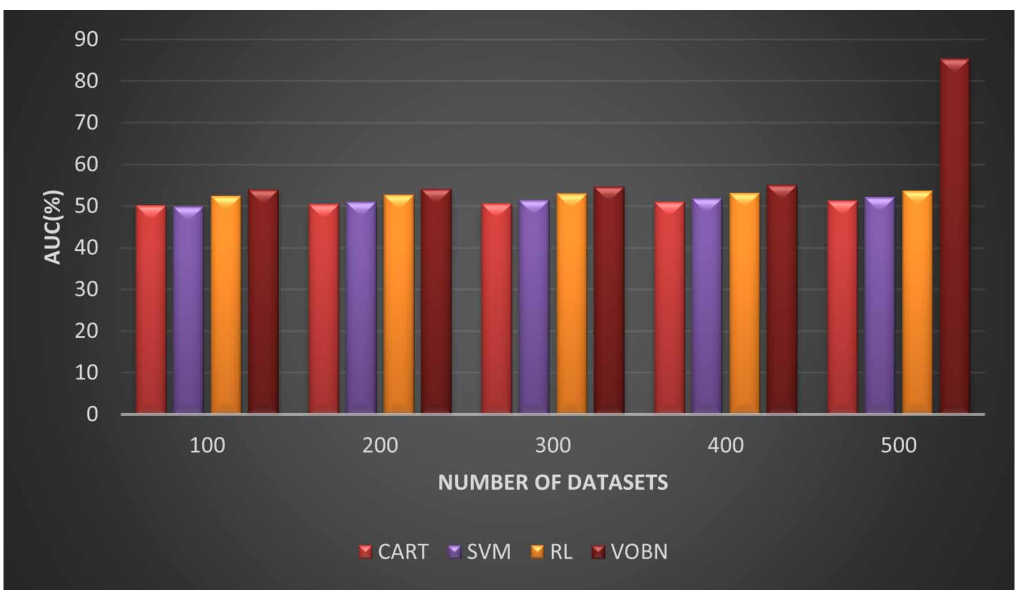


Figure 7 shows a comparison of AUC between existing CART (Classification and Regression Tree), SVM(Support Vector Machine), Reinforcement Learning (RL) methods, and the proposed variable-order Bayesian network (VOBN) method where the X-axis indicates a number of datasets and y-axis represents the AUC in percentage. The orange-red color indicates CART, violate color indicates SVM, the light green color indicates RL, and the teal color indicates the proposed VOBN technique. The orange-red color indicates CART, violate color indicates SVM, the light green color indicates RL, and the teal color indicates the proposed variable-order Bayesian network (VOBN) technique. When compared, existing CART (Classification and Regression Tree), SVM(Support Vector Machine), Reinforcement Learning (RL)methods achieve 50.7%, 51.28%and 52.94%while the proposed VOBN method achieves 54.66%which is 4.16% better than CART,3.42% better than SVM and 2.32% better than RL.

Table 7 shows a comparison of ROC between existing CART, SVM, and RL methods and the proposed VOBN method.

Table 7. Comparison for ROC

Number of datasets	CART	SVM	RL	VOBN(proposed)
100	39.7	42.1	44.1	45.4
200	40.1	42.4	44.4	45.7
300	40.5	42.7	44.6	45.9
400	41.1	42.8	44.9	46.1
500	41.6	43.2	45.1	46.5

Figure 8. Comparison of ROC

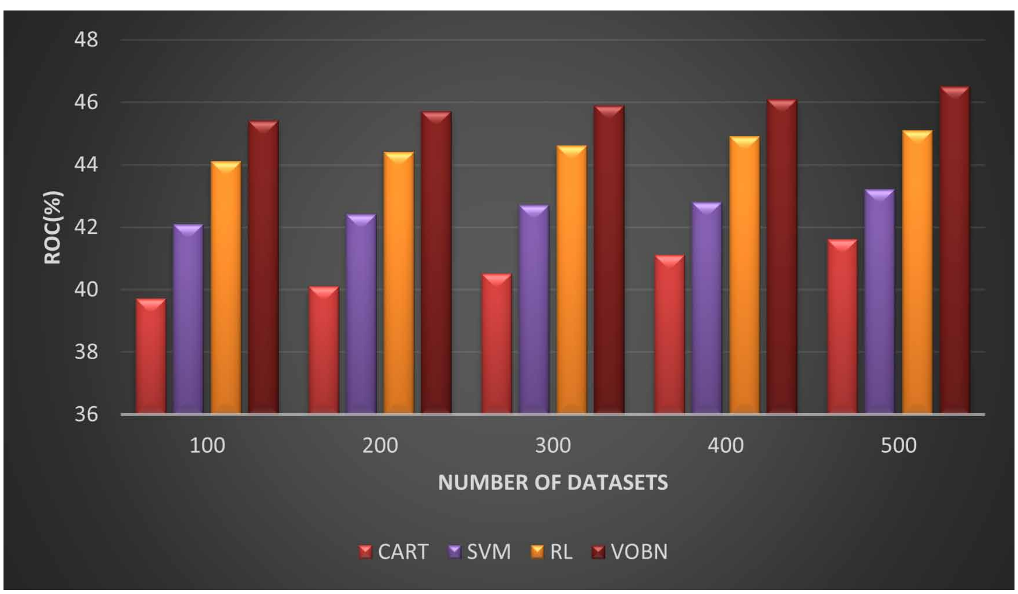


Figure 8 shows a comparison of ROC between existing CART (Classification and Regression Tree), SVM(Support Vector Machine), Reinforcement Learning (RL) methods, and the proposed variable-order Bayesian network (VOBN) method where the X-axis indicates a number of datasets and y-axis represents ROC in percentage. The orange-red color indicates CART, violate color indicates SVM, the light green color indicates RL, and the teal color indicates the proposed VOBN technique. When compared, existing CART (Classification and Regression Tree), SVM(Support Vector Machine), Reinforcement Learning (RL) methods achieve 40.6%, 42.64%and 44.62%while the proposed VOBN method achieves 45.92%which is 5.32% better than CART,3.32% better than SVM and 1.3% better than RL.

Table 8 shows the overall comparative analysis between existing CART, SVM, and RL methods, and the proposed VOBN method.

Table 8. Overall comparison between the existing and proposed method

Parameters	CART	SVM	RL	VOBN(proposed)
Accuracy(%)	94.18	94.74	96.24	97.1
Precision (%)	93.02	93.92	94.84	96.2
Recall (%)	85.24	86.8	88.66	89.8
F1-Score (%)	79.72	81.82	83.1	84.82
AUC (%)	50.7	51.28	52.94	54.66
ROC (%)	40.6	42.64	44.62	45.92

Figure 9. Overall comparison of proposed and existing techniques

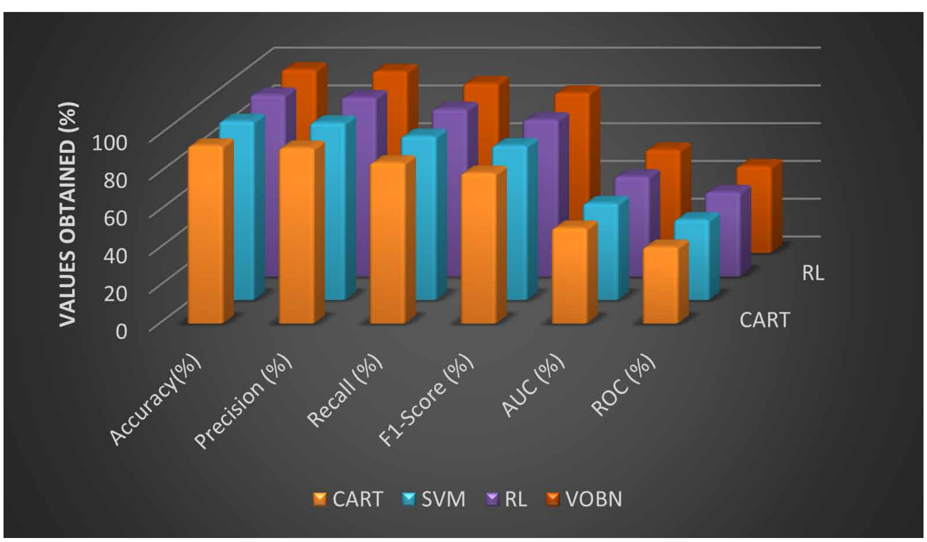


Figure 9 shows an overall comparison between the existing Classification and Regression Tree (CART), Support Vector Machine (SVM), Reinforcement Learning (RL) methods, and the proposed VOBN method where X-axis indicates parameters and the y-axis represents values obtained by all methods in percentage. When compared to existing techniques such as CART (Classification and Regression Tree), SVM(Support Vector Machine), and Reinforcement Learning (RL) proposed method VOBN achieves better results. Average obtained by proposed VOBN technique is accuracy 97.1%, precision 96.2%, recall 89.8%, F1_score 84.82%, AUC 54.66% and ROC 45.92%.

CONCLUSION

SCD is one of the main causes of death. Every day thousands of patients die because they are not treated on time. Higher anticipation of an SCD episode is vital so medical specialists can apply the timely treatment, increasing the possibility of surviving the event. In this work, a new methodology based on machine learning algorithms namely variable-order Bayesian network is presented for SCD prediction using attributes. In addition to presenting an experimental evaluation for validating the methodologies of prediction of SCD avoiding misclassification due to features that do not belong to the SCD event. The Variable-order Bayesian network produced a graphical representation of the dependencies. The experimental result is done using the parameters such as accuracy, precision, recall, F1-score, AUC, and ROC. It is found that the proposed VOBNattains 97.1% of accuracy, 96.2% of precision, 89.8% of recall,84.82% of F1-score, 54.66% of AUC, and 45.92% of ROC. The future work concentrates on extending the framework by including an online apache spark streaming process for data-preprocessing the dataset.

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Chapter 9
Utilization of Artificial Intelligence-Based Wearable Sensors in Deep Residual Network for Detecting Heart Disease

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ABSTRACT

Recently, there has been growing attention to the advances in the areas of electronic and biomedical engineering and the great applications that these technologies can offer mainly for health diagnosis and monitoring. In the past decade, deep learning (DL) has revolutionized traditional machine learning (ML) and brought about improved performance in many fields, including image recognition, object detection, speech recognition, and natural language processing. This chapter discusses detection of heart disease using deep learning techniques. Here the input data has been collected based on wearable device-collected data with IoT module. This data has been preprocessed using adaptive histogram normalization, and the authors segment the image based on threshold method using Ostu thresholding technique. The segmented image feature has been extracted using generative adversarial network and classification of extracted features using deep residual network. The experimental analysis is obtained by the proposed GAN_DRN in terms of accuracy as 96%, precision of 85%, recall of 80%, F-1 score of 71%, and AUC of 75%.

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INTRODUCTION

With the growing global population and recent changes in human lifestyles, people with complex medical illnesses are on the rise. This has increased the number of individuals visiting hospitals, putting a strain on the Medicare healthcare system. As a result, there is a growing demand for remote health care systems that can help with these issues. Recently, there has been an increased focus on advancements in the fields of electrical and biomedical engineering, as well as the numerous applications that these technologies can provide, particularly in the areas of health diagnosis and monitoring. Many individuals worldwide now have access to smartphones and wearable sensors at low prices. When combined with artificial intelligence approaches, these gadgets can be used to monitor and diagnose patients with heart ailments, minimizing hospital visits and enhancing people's lives (Jiang et al., 2021).According to AHA (American Heart Association), heart disease, also known as CAD (coronary artery disease), is a term utilized to describe a variety of problems caused by plaque buildup in the walls of arteries, which causes the arteries to gradually narrow, making blood flow difficult and enhancing the risk of heart attack and stroke (Awotunde et al., 2021). Deep convolution neural network (CNN)-based techniques for authentic arrhythmia detection were used (Wu et al., 2020). Firstly, they created a deep convolution network model with higher levels. This model achieved stranded state-of-the-art performance on the PhysioNet/CinC AF Classification Competition 2017 dataset with the assistance of pre-processing. Systems with poor computer resource needs are preferable. A binarized model utilizes substantially less computational speed and storage space than a full-precision model, according to research. Using a Cascaded Convolution Neural Network (CCNN) and subjective description manner, (Yang et al., 2021) offers a 12-lead ECG arrhythmia classifier model. First and foremost, the one-dimensional (1-D) CNN is intended to automatically remove the features from the individual lead indicator. Following that, features are concatenated as a contribution to two-dimensional (2-D) densely linked ResNet modules for categorizing the arrhythmia, taking into account temporal relationships and spatial scales among different leads. CAD was a major cause of death globally in 2010, accounting for one out of nine deaths in the United States. People with HD (heart disease) may experience chest discomfort and exhaustion. However, many people have no symptoms until they have a heart attack (Ali et al., 2021).This was the primary motivation for evolving a smart method that can continuously monitor a person's heart as well as alert them to any heart-related issues. AI is a branch of computer science that tries to replicate human cognition in activities like object or pattern identification, planning, and problem-solving. The term "big data" refers to massive, heterogeneous data volumes that necessitate the use of computer tools such as AI to analyze and interpret. This comprises omics data, tabular data from electronic health records, and imaging data in health care. Individual measurable qualities or data points known as features exist inside big data. The quality, accuracy, and diversity of data elements are all important factors in AI model success.ML, a subfield of AI, allows computer techniques to learn as well as enhance over time by exposing them to large volumes of data. While there are numerous algorithmic approaches or models in machine learning, they always strive to accomplish one of two goals. First is supervised learning, which involves using a labeled data set to forecast a specific outcome. This entails selecting and weighting specific features iteratively in order to identify underlying patterns in data that best fit the outcome. Linear regression, SVM, and RF are examples of supervised learning techniques. Clustering and principal component analysis are examples of models that aim to capture correlations inherent in the structure of features themselves. DL is a type of ML that makes predictions directly from input data using multilayered ANN.CNNs are the most often utilized deep learning networks for image processing. Some of the most significant achievements of

DL in health care are in the field of computer vision, which deals with tasks like object categorization, detection, and segmentation from digital images or videos. Before being fed into the CNNs, raw picture data is usually converted into features. Another new use of DL is for analyzing tabular data from EHRs in order to make per-patient predictions. This comprises both organized and unstructured data that requires standardization and sequencing, such as test findings, diagnostic codes, and demographics. The process of obtaining millions of computational quantitative features from medical images is referred to as radionics. By expressing textural patterns or geometric attributes within a given imaging region of interest, these features represent complicated spatial interactions between voxels. These data sets can then be subjected to machine learning algorithms in order to uncover imaging biomarkers with clinical significance.AI algorithms can be utilized in cardiovascular imaging to both uncover new imaging biomarkers as well as combine data from a variety of sources to give patient-specific risk prediction.

Furthermore, using clever ML (machine learning) techniques, the proposed system can quickly diagnose the presence of an HD condition. There are numerous advantages to using wearable technology for medical purposes, particularly for patients with CAD. The ability to remotely monitor CAD patients is a major benefit of these devices. Patients will be able to live a more autonomous and simple life due to this benefit. Furthermore, these devices may detect cardiac instability in real-time, allowing for an immediate response, which is critical because only a few minutes can save a person's life with heart illness (Ali et al., 2020).

Furthermore, because many patients live in rural areas and have limited access to health care, the creation of such systems can aid in ongoing remote monitoring for these people, resulting in fewer hospital visits. Add to that the system's sophisticated diagnostic capability, which can help in the early detection and analysis of cardiac disease. Furthermore, due to recent improvements in consumer electronics and mobile devices, which have cut production costs and allowed regular users to afford inexpensive sensors and mobile phones, remote health diagnosis, and monitoring systems are affordable to many people (Faizal et al., 2021).

As stated in the related work section below, numerous systems are developed to predict as well as diagnose CVD using data mining approaches and hybrid models. Risk factors are extracted from unstructured textual data using a data mining technique. Furthermore, a hybrid model is a combination of two or more strategies that operate better together than they do separately. There are two key phrases in these hybrid models. The feature's subset or weight is used as input for classifiers to forecast cardiac disease in the second phase. A gathered dataset on HD, on the other hand, comprises both useful and redundant, and irrelevant characteristics. Handling these features is not only time-consuming, but it also has an impact on classification accuracy. ML has advanced enormously as its approaches have become more popular and widely available. Face identification, system security, disease diagnosis, medication research, and a slew of other groundbreaking applications influenced the lives of countless people. Building ML apps are based on a different principle than most traditional programming methods. ML models, in essence, learn from patterns in provided training samples without the use of explicit instructions and then utilize inference to make valuable predictions. Some ML techniques, such as ANN and SVM, are well-known as successful prediction techniques, however, they are not without flaws. The fundamental issue is that they remain as black boxes once the method is completed. Prediction models are typically created utilizing historical data to generate forecasts about future events that may occur. Understanding the reasons behind method prediction response could save businesses' stakeholders a lot of time and effort as they investigate various circumstances, such as selecting the appropriate medical treatment or assessing the risk of investment plans. Fewmodelled ML techniques play an important part in the healthcare system and designed methods may advise a patient to undergo surgery. To avoid life-threatening scenarios, that judgment must be highly precise. Before proceeding with the procedure, it is necessary to have a clear grasp of the reasons for the model's final advice. Patients' data sets must be used to develop ML models capable of performing heart patient diagnoses. Most academics collect data for analysis on a few trusted platforms, such as UCI and Kaggle. The Cleveland HD data set, which originally consisted of 76 characteristics and has 303 cases, was used in this study and can be found at the UCI_ML Repository. The information was obtained from the Cleveland Clinic Foundation in Cleveland, Ohio, and provided by Robert Detrano, M.D., Ph.D. of Veterans Administration Medical Center in Long Beach, California.

Furthermore, current techniques for diagnosing heart disease rely on broad feature weighting approaches. These techniques assign the same weight to each characteristic. They do, however, use unreliable combination processes, which could influence the feature importance for differentiation. Due to a lack of theoretical foundation, they raise MSE (mean square error) as well as reduce the accuracy of the prediction method. As a result, before using classification models, it is required to remove unnecessary features as well as assign a certain weight to characteristics. DL has transformed traditional machine learning over the last decade, resulting in better performance in various disciplines, including image identification, object detection, audio recognition, and NLP.HAR's performance and resilience have been increased thanks to DL, which has accelerated its adoption as well as application to a wide range of wearable sensor-based applications. There are two major reasons why DL is useful in so many situations. DNNs can significantly learn representative features from raw inputs with limited domain expertise. DL has witnessed a significant increase in HAR-based applications due to its expressive power. There were four heart disease data sets to choose from on the UCI website: Hungarian and Cleveland data sets were the most promising. The Cleveland data set, in particular, was nearly complete with 303 occurrences, whereas the Hungarian data set contained 294 examples, although some features, such as slope, ca, and that, were missing. Other 2 data sets, Switzerland and Long Beach, on other hand, had 123 and 200 cases, respectively, and even more missing features like chol, exacting, and thalach. After reviewing various HD data sets, it's time to take a closer look at two big data sets with the most records: Cleveland and Hungarian data sets. Distribution of cardiac disease categories in the Hungarian data set was proportionate, whereas several disease categories, such as Dis-Cat1 were overrepresented in the Cleveland land data set. Almost all of the studies done on heart data sets combined all of the illness categories. As a result, the note was unimportant, and the Cleveland data set won the vote for which data set to utilize. This resulted in an almost balanced group of illnesses against no-disease cases: 160 cases of people without HD versus 137 cases of people at risk of heart disease. Only 13 of the initial 76 features were employed in most research publications that looked into the Cleveland data set. The data set's final column is num, which is a categorical variable with values of 0 for no disease and 1, 2, 3, and 4 for various levels of HD.HD variation levels 1 to 4 are not stated in the UCI public data sets description, as previously mentioned. Because it seemed reasonable to group all disease levels 1, 2, 3, and 4 into one category in this study, the num variable only had two options: Dis or NoDis. (Albahriet al., 2021).

This chapter discusses the detection of heart disease using deep learning techniques. Here the wearable sensor-based input data has been pre-processed using adaptive histogram normalization and segment the image based on the threshold method using the Otsu thresholding technique. The segmented image feature has been extracted using a generative adversarial network and the classification of extracted features using a Deep Residual Network.

The research organization is as follows: section 2 compares existing review works. Section 3 introduces the proposed heart disease detection architecture. Section 4discuss the performance analysis. Section 5 concludes the chapter with future scope.

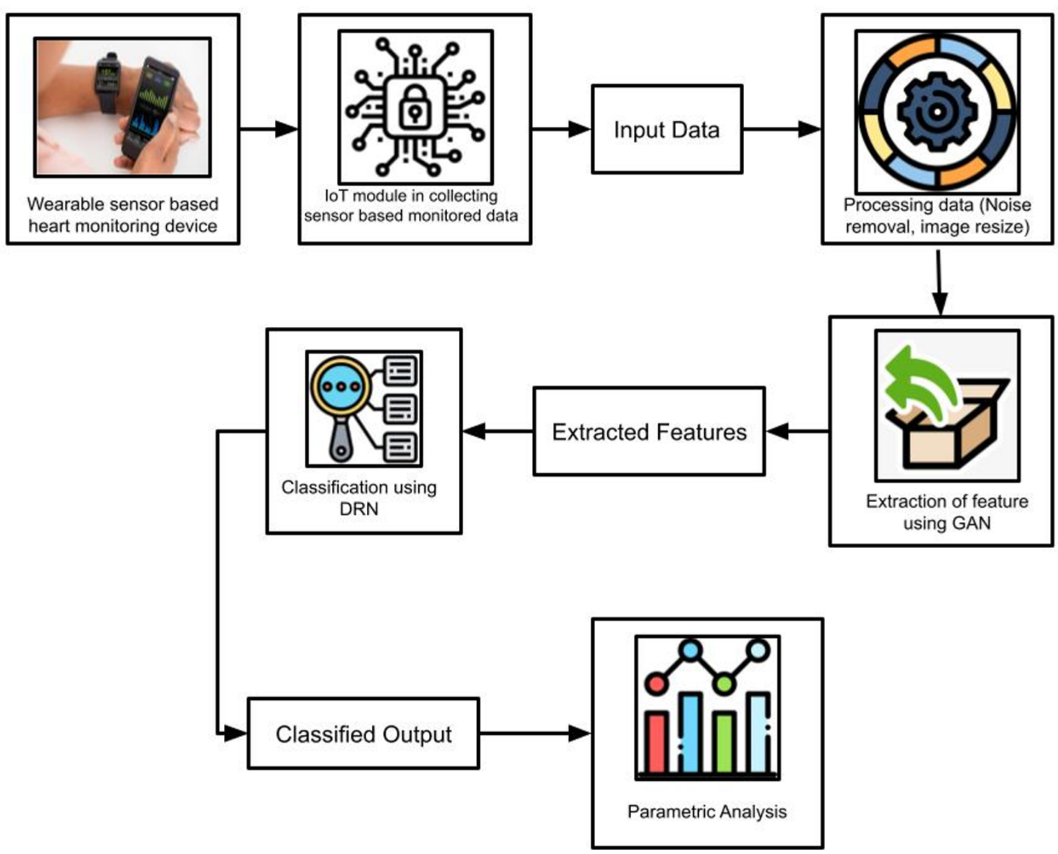
RELATED WORKS

According to Al-Makhadmeh et al., 2019 AI technique has built wearable gadgets like fitness bands and intelligence platforms to track pulse rates, motion activities and heart rate in this age of AI.AI's impact on wearable gadgets highlights fact that smart knowledge is utilized to develop devices that find intelligence in body language as well as movements. Gadgets' speed, as well as accuracy, are geared to provide precise measurements of heart rates, physical reaction, and energy levels to diagnose CVD. According to (Nandy et al., 2021), the speed and accuracy of wearable gadgets have helped sustain significance in healthcare delivery systems. Large volumes of physiological data can now be recorded thanks to monitoring technology. The processing capacity of mobile phones has been demonstrated, allowing MLAs to be supported. MLA is used to analyze psychological data in CVD monitoring (Ribeiro et al., 2021). Deep convolution neural network (CNN)-based techniques for authentic arrhythmia detection were used (Wu et al., 2020). Firstly, they created a deep convolution network model with higher levels. This model achieved stranded state-of-the-art performance on the PhysioNet/CinC AF Classification Competition 2017 dataset with the assistance of pre-processing. Systems with poor computer resource needs are preferable. A binarized model utilizes substantially less computational speed and storage space than a full-precision model, according to research. Using a Cascaded Convolution Neural Network (CCNN) and subjective description manner, offers a 12-lead ECG arrhythmia classifier model. First and foremost, the one-dimensional (1-D) CNN is intended to automatically remove the features from the individual lead indicator. Following that, features are concatenated as a contribution to two-dimensional (2-D) densely linked ResNet modules for categorizing the arrhythmia, taking into account temporal relationships and spatial scales among different leads. The Heart To Go gadget collects data and classifies ECG readings. Heart To Go is a mobile phone that is used to do data collecting, as well as the extraction as well as classification of ECG signals (Manimurugan et al., 2022). By amplifying monitored input data, the CVD monitoring method is improved. Another major issue for an HDD system is the extraction of useful features from medical textual data as well as the merging of sensor data. Feature extraction techniques extract useful data from large amounts of healthcare data. Data fusion is a method of combining data from several sources to provide useful and relevant information. Recently, various approaches have been developed to extract features from healthcare textual data (Ramasamy et al., 2022) and fuse sensor data with other data (Muthu et al., 2020). A real-time method based on ML classifiers was described (Ganesan et al., 2019). This system uses two separate feature extraction algorithms to extract an important characteristic from the healthcare dataset. To mine EMRs for HDD, a unique and robust framework was provided. This system employs a word embedding model to identify features and an LSTM to forecast heart failure. Another technique (Lin et al., 2019) used echocardiography findings to predict the death rate of cardiac patients in hospitals. This method extracts characteristics using text mining techniques before using a DL model to forecast death rates. To extract data from EMRs, a unique text mining approach is described (Wang et al., 2022). This system's creators use a rules-based engine to automate data extraction as well as decision-making. Furthermore, using unstructured EMRs of patients, an HD risk score is developed (Iqbal et al., 2018). The inventors of this system utilize text mining algorithms to identify heart-critical parameters from unstructured EMRs as well as create a risk score for HD in diabetic patients. For music recommendations, wearable sensors monitor users' emotions (Wu et al., 2020). The authors used feature-level fusion in this system, which pulls data from every sensor separately and then combines them for emotion recognition. Scientists used both environmental as well as wearable body sensors for emotion detection in another method(Li et al., 2020).To explore the impact of the environment on human health, they used all 3 degrees of fusion. To predict illness risk, an RCNN-based method was presented (Ihnaini et al., 2021).To increase the accuracy of the RCNN, this method gathers features from patients' structured as well as unstructured data and combines them by utilizing DBS.

PROPOSED DESIGN IN HEART DISEASE DETECTION USING DEEP LEARNING TECHNIQUES

This section discusses proposed heart disease detection utilizing DL methods based on wearable sensor data. Here the input data has been collected based on wearable device collected data with the IoT module. This data has been preprocessed using adaptive histogram normalization and segmented the image based on the threshold method using Ostu thresholding technique. The segmented image feature has been extracted using a generative adversarial network and the classification of extracted features using a Deep Residual Network. The overall proposed architecture is shown in figure-1.

Figure 1. Overall proposed architecture



Smartwatches have begun to be released by big electronics companies as well as new start-ups in recent years. In September 2013, the Samsung Galaxy Gear was one of the first devices to be released. The Apple Watch was released in April 2015, about a year later. The majority of suggested health-monitoring frameworks use a 3-layer architecture: WBAN with wearable sensors as data acquisition unit, communication, networking, and a service layer. Through Wireless Bluetooth communication, a microcontroller sends acquired medical data to an Android App. The Android app saves the user's heart rate on a cloud server and the user can view data via the Android app. Using the DL module in the android/desktop app, the user confirms whether he has coronary HD or not. A wearable computer is created using the built-in feature. Modern embedded systems are built primarily on an integrated microcontroller pulse sensor and other modules, pulse sensor based on PPG technique, and other peripheral devices with a certain purpose. PPG sensors use the light-based technique to control the heart's pumping action-controlled blood flow rate. We've included a Bluetooth model for connecting with the Android app and providing BPM beats per minute, as well as an LCD panel for reading BPM on wearable devices. Proposed architecture is put into action by creating a "Pulse Sensor Library" that handles ADC analog to digital converter interfaces and TIMER with microcontrollers. The LED produces light that falls directly on the vein. Only while the heart is pumping (systolic) will vein have higher blood flow inside them, and when the heart is not pumping (diastolic), therefore if monitor blood flow, can also monitor the heartbeats. Analogue and digital converter (ADC) starts reading an analog signal at the T point, which represents received the light of blood flow. Threshold Value 'T' is specified as a start point for each beat (25 percent or 50 percent) of the signal. This action was accomplished via an INTERRUPT mechanism, which halted the microprocessor every 2 ms for reading from the sensor. To calculate our heartbeats in minutes, take an average of 10 or more beats.

ADAPTIVE HISTOGRAM NORMALIZATION BASED PRE-PROCESSING

The picture improvement has been achieved to acquire the same grey levels with uniform, smooth, and translated by histogram for pixel mapping of grey level, by contrast, adaptive histogram equalization based on probability theory. According to the physics definition of a histogram, every bar in an equalized histogram has the same elevation. Equation eq (1),

$$p_s(s)ds = p_r(r)dr \tag{1}$$

Assume that s=T(r) is a gradually maximizing interval function, and that its inverse, r=T- (s), is also a monotonic operation by eq. (1)

$$p_s\left(s\right) = \left[p_r\left(r\right)\frac{1}{ds/dr}\right]_{r=T^{-1}(S)} = p_r\left(r\right)\frac{1}{p_r\left(r\right)} = 1 \tag{2}$$

RELATIONSHIP FOR MAPPING IN CONVOLUTIONAL HISTOGRAM EQUALIZATION ALGORITHM

As for discrete states, correlation among i and *fi* by eq. (3)

$$f_i = (m-1)T(r) = (m-1)\sum_{k=0}^{i}\frac{q_k}{Q} \tag{3}$$

Where m is image grey intensity, *qk* is image pixel with gray level k^{th}. *Q* is totalimage pixels. If an image has *n* various gray intensities and the occurrence probability of i^{th} gray intensity is *pi,* so the entropy of gray intensity is given as eq. (4)

$$e(i) = -p_i \log p_i \tag{4}$$

Complete image entropy is given by Eq. (5)

$$E = \sum_{i=0}^{n-1} e(i) = -\sum_{i=0}^{n-1} p_i log p_i \tag{5}$$

It is proved that *E* will attain its greatest if and only if $p_0 = p_{12} = \ldots = p_{n-1} = \frac{1}{n}$. The entropy of the entire image is maximized and the histogram in the image has been evenly dispersed. After equalization, which is extended by dynamic range, it is more appropriate (3). To increase quantization of equalization interval.

OSTU THRESHOLDING BASED SEGMENTATION

The technique of separating the iris from collected data is critical since it defines which section of the brain is the most valuable to process further. If the segmentation isn't done correctly, the system's subsequent stages will generate incorrect data, affecting the system's overall performance. The suggested work uses OTSU's approaches, which often attain higher accuracy while detecting by Eqn (6).

$$\sigma^2 = \frac{\sum_{i=0}^{N}(X_i - \mu)^2}{N} \tag{6}$$

Where, X_i is image pixel value, μ is the mean and N is several pixels in one image.

OSTU's approach is utilized in different image processing applications that perform histogram-based picture thresholding or convert grayscale images to binary. Image is divided into 2 intra-classes to determine the best threshold. To investigate the threshold values that minimize the intraclass variation defined by the weighted sum of variances of two courses in eq. (7):

$$\sigma_{\omega}^{2}\left(t\right)=\omega_{0}\left(t\right)\sigma_{0}^{2}\left(t\right)+\omega_{1}\left(t\right)\sigma_{1}^{2}\left(t\right) \quad (7)$$

Where, $\omega 0$ and $\omega 1$ $_a$re weights probabilities of 2 class which is separate by threshold t, σ_0^2 *and* σ_1^2 are the variance of two classes.

OSTU defines minimization of intra-class variance as eq. (8), (9), which is equivalent to maximization of inter-class variance

$$\sigma_{b}^{2}\left(t\right)=\sigma^{2}-\sigma_{\omega}^{2}\left(t\right) \quad (8)$$

$$=\omega_{1}\left(t\right)\omega_{2}\left(t\right)\left[\mu_{1}\left(t\right)-\mu_{2}\left(t\right)\right] \quad (9)$$

t histogram eq. (10) is used to determine the class probabilities $\omega 1_{(}t)$:

$$\omega_{1}\left(t\right)=\sum_{0}^{t}P\left(i\right) \quad (10)$$

Class probabilities $\mu 1_{(}t)$ is represented as Eq. (11):

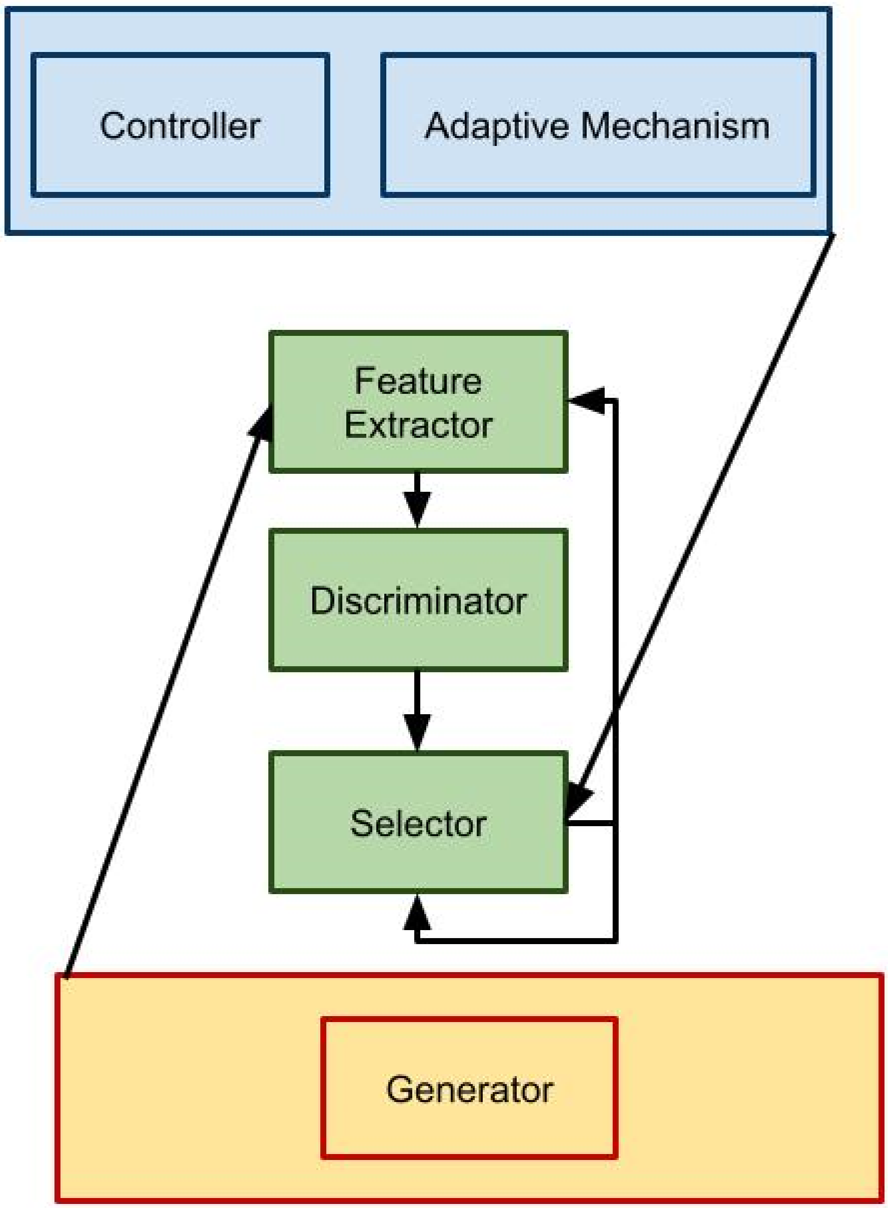
$$\mu_{1}\left(t\right)=\sum_{0}^{t}P\left(i\right)x\left(i\right) \quad (11)$$

Where x(i) is the histogram bin center value.

GENERATIVE ADVERSARIAL NETWORK-BASED FEATURE EXTRACTION

A selector, discriminator, and feature extractor are three components of a GAN. Multiple generators are included in the feature extractor. A controller, as well as an adaptive method, are included in the selection. The feature extractor in this framework extracts feature vectors of various dimensions. To score the feature results, the extracted feature vectors are sent to the corresponding discriminator. By fooling the discriminator, the feature extractor learns not just to extract dimensional characteristics through conventional supervised training, but also to extract features with improved generalizability. The selector is used to alter the network's coordination. The selection can also be used to choose which dimensions features are taken into account adaptively. The general architecture of GAN is shown in figure-2.

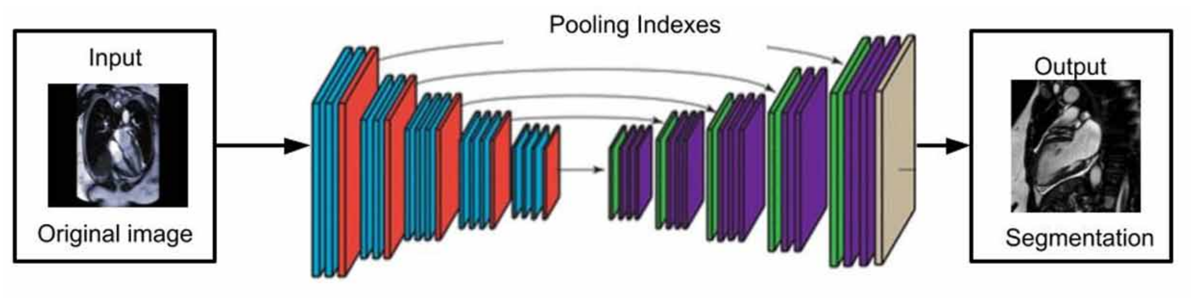
Figure 2. The general architecture of GAN



The feature extractor, as well as discriminator settings in this approach, are partially related to the deployment of a GAN. The original GAN model's main goal is to generate images by fitting the corresponding generator as well as discriminator functions. There are no restrictions on generator and discriminator's specific structures. The feature extractor, as well as the discriminator in this research, are both based on NN models due to the great successes of DNN in image processing. Simultaneously, the features extracted in 2D are integrated to improve segmentation accuracy following adaptive selection, to better retain image information. The following sections provide a full explanation of the framework's composition and algorithms for each component.

Feature Extractor: There are multiple feature generators in the feature extractor. The extractor's goal is to build a new segmented image by extracting deep image features at several layers. The coordination of two networks is used to demonstrate the adaptable architecture presented in this research. As a result, two generators are presumed to be present in the feature extractor. As illustrated in Figure 3, the network architectures of these two generators are identical.

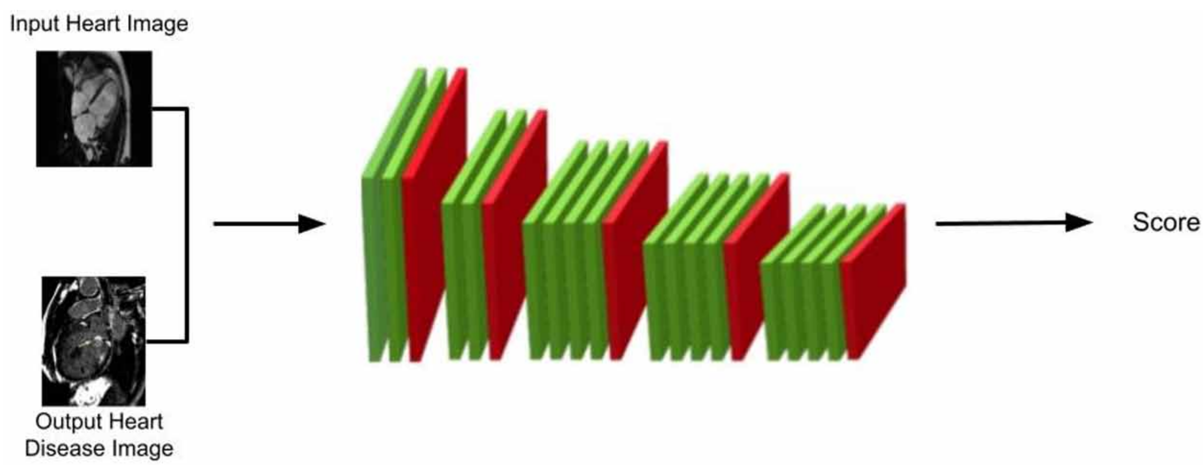
Figure 3. Network structures of two generators



The two generators in the encoder first execute Conv operations on the input picture with a $3 \times 3 \times 32$ convolutional layer and a $5 \times 5 \times 32$ convolutional layer, respectively. Second, batch normalization operations are conducted in each convolutional layer after picture convolution to avoid training failure caused by value shifts in image distribution after convolution or during iteration. Finally, the network performance is optimized linearly using the ReLU activation function. A $2 \times 2 \times 2$ maximum pooling procedure is conducted after the above 3 steps have been repeated 2 or 3 times. Because convolution kernels of 2 generators are of different sizes, the original image's detailed information is recovered in several dimensions. Number of convolution kernels is doubled every time, while the size is cut in half. The retrieved features enter the decoder after five encoding cycles. A 2×2 upsampling operation is performed first in the decoder. Images obtained by copying as well as cropping before the maximum pooling layer are then stitched together, as is the image created by deconvolution in the corresponding layer. Finally, in the matching layer, the identical convolution, as well as batch normalization processes, are conducted. Stitching, deconvolution, convolution, and batch normalization processes are performed 2 or 3 times. Results are then passed on to the next layer. Every time, the number of Conv kernels is cut in half, and the size is increased by a factor of two. Changes to parameters for the next iteration are guided by loss. The input to the sigmoid layer is the output of the penultimate layer. The features are then put through a binary classification process.

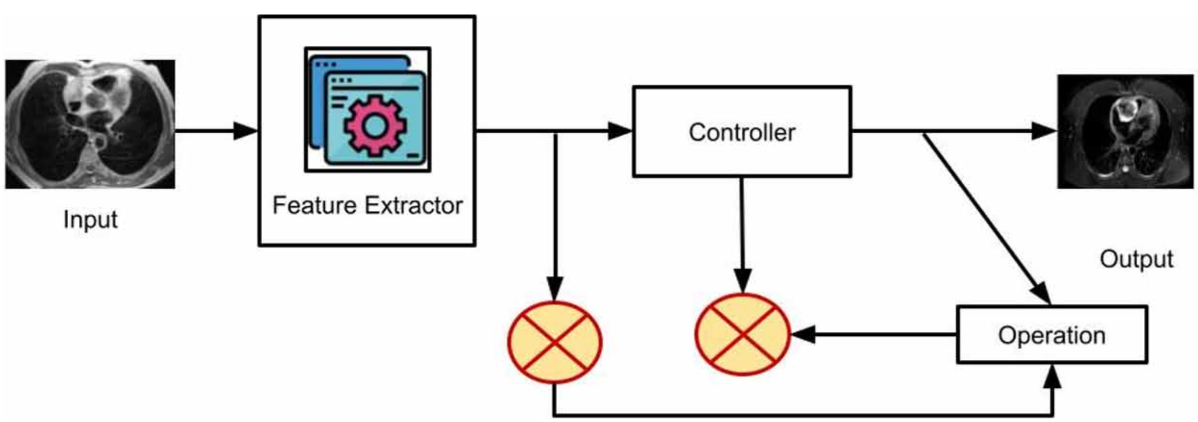
The network discriminator is utilized to determine if a particular segmentation result is an actual result or a model forecast. If the discriminator has a high level of discrimination but can't tell the difference between projected and actual results, the prediction method has a good expression or prediction capacity. Because GAN's feature extractor has 2 generators, a discriminator is utilized to assess the quality of these 2 generators as well. Discriminator in GAN uses the same discrimination method for each generated result as the discriminator in a GAN is represented in Figure 4.

Figure 4. Discriminator of GAN



Adaptive rules are used by the selector during the dynamic training process to choose appropriate features as well as alter the network training process and training parameters. Adaptive control rules are built on top of the discriminator's scores. Figure 5 depicts the structure of the selector.

Figure 5. Selector structure



GANs' training mechanism can be thought of as two players in a min-max game playing against each other. Each player aspires to outperform the others and emerge victoriously. We define the optimization problem defining the G and D interplay based on this analogy, as indicated in eq. (12):

$$\min_{\theta}\max \gamma' L\left(G_{\theta}, D_{\gamma}\right)$$
$$= E_{x,y \Rightarrow p(x,y)}\left[\log D_{\gamma}\left(x, y\right)\right] + E_{y \Rightarrow p(y), z \Rightarrow p(z)}\left[\log\left(1 - D_{\gamma}\left(G_{\theta}\left(y, z\right), y\right)\right)\right] + \lambda L_{DEV}\left(G_{\theta}\right) \quad (12)$$

Here λ is a trade-off constant and λ > 0. This final term is used to ensure that the synthetic image generated by the generator does not stray too far from the genuine image. It's a simple L1 loss function, indicated by the symbol eq. (13):

$$L_{DEV}\left(G_\theta\right) = -\sum_i \log D_\gamma\left(G_\theta\left(y_i, z_i\right), y_i\right) + \lambda x_i - G_\theta\left(y_i, z_i\right)_1 \tag{13}$$

During training, the generator attempts to create realistic-looking synthesized images to deceive the discriminator and allow the discriminator to categorize the created images as real. The generator accomplishes this by minimizing our objective function, equation 1. In practice, this may be accomplished using the approximation approach by minimizing $\log D_{\gamma(}G\theta_{(y}i,_{z}i)\, yi)_{,}$ which is a simpler form than the original 1–logD$\gamma(_{G\theta}(y_{i,} zi_{,} y_{i})$. $_T$he overall generator loss is given by Eq. (14):

$$L_G\left(G_\theta\right) = -\sum_i \log D_\gamma\left(G_\theta\left(y_i, z_i\right), y_i\right) + \lambda x_i - G_\theta\left(y_i, z_i\right)_1 \tag{14}$$

Discriminator D, on the other hand, maximizes the objective function in order to accurately classify and differentiate synthesized images from real ones. Equation (15) determines the discriminator loss:

$$L_D\left(D_\gamma\right) = \sum_i \log D_\gamma\left(x_i, y_i\right) + \log\left(1 - D_\gamma\left(G_\theta\left(y_i, z_i\right), y_i\right)\right) \tag{15}$$

Here, X = ˆx or X = xs. |λs$_|$ denotes the total number of interest feature mappings in the current layer λs. Let i and j be the indexes of interest feature maps, and k be the index of a current feature map element. The Gram matrix $G_{\gamma_m}^{\lambda_x}\left(X\right)$, which belongs to $R^{|\lambda_*|\times|\lambda_*|}$, is used to characterize the information of the corresponding feature. Each element $G_{\gamma_\alpha, ij}^{\lambda_*}\left(X\right)$ in the λ_s^{th} layer of block γs defines an inner product of the ith and jth interest feature maps. Equationally, from eq (16),

$$G_{\gamma_{x,ij}}^{\lambda_z} = \sum_k \phi_{\gamma_{\alpha,ik}}^{\lambda_z} \phi_{\gamma_{a,j}k^*}^{\lambda_z} \tag{16}$$

During training, the style loss of x_s and x' is defined as eq. (17):

$$l_{sty}\left(G_\theta\right) = \sum_{\gamma_n \in "_n, \lambda_n \in \rangle_*} \frac{\omega_{\gamma_z}}{W_{\gamma_n} H_{\gamma_n}} \times G_{\gamma_\theta}^{\lambda_n}\left(x_s\right) - G_{\gamma_s}^{\lambda_z}\left(x'\right)^2 F^* \tag{17}$$

$\|\bullet\|_F$ is the Frobenius norm of the matrix, and ϖ_{γ_s} is the weight of the γs th block Gram matrix. Note that by definition $x' = G_\theta\left(y, z\right)$ as represented in eq. (18).

$$l_{\text{cont}}\left(G_\theta\right)=\sum_{\gamma_c \in “_e, \lambda_e \in ›_e} \frac{1}{W_{\gamma_e} H_{\gamma_e}} \phi_{\gamma_e}^{\lambda_e}\left(x\right)-\phi_{\gamma_e}^{\lambda_c}\left(x'\right)_{F'}^{2} \tag{18}$$

Total variational loss: For spatial smoothness of the generated images, it is incorporated using the following equation, as indicated in eq (19).

$$l_{tv}\left(G_\theta\right)=\sum_{w,h}\left(x'_{w,h+1}-x'_{w,h}{}^{2}{}_{2}+x'_{w+1,h}-x'_{w,h}{}^{2}{}_{2}\right) \tag{19}$$

$x'_{w,h}$ specifies the pixel value of a point in the created image x', where w,hÎW, H. When all three loss functions are added together, we get Style Loss $L_{ST}(G_{\theta)}$ as eq (20),

$$L_{ST}\left(G_\theta\right)=\omega_{cont} l_{cont}+\omega_{sty} l_{sty}+\omega_{tv} l_{tv}. \tag{20}$$

So, we replace L DEV in equation 1 with this type of transfer loss L, and the new goal function for generator G is

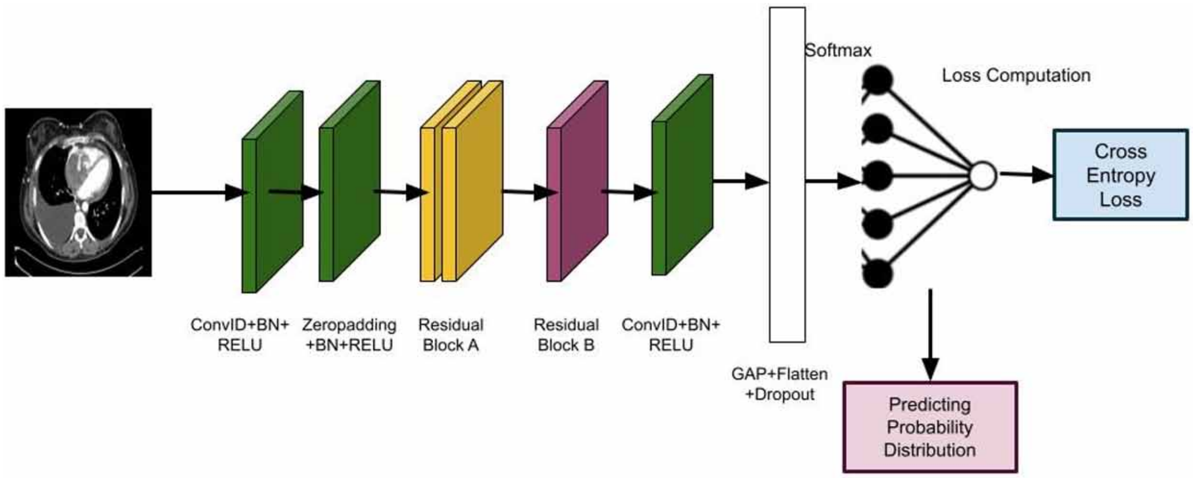
$$L_G\left(G_\theta\right)=-\sum_i \log D_\gamma\left(G_\theta\left(y_i, z\right)\right)+L_{SEG}\left(G_\theta\right)+L_{ST}\left(G_\theta\right).$$

The objective function of the discriminator has not altered. Back-propagation optimization of the aforesaid goal function is used to acquire style transfer from input style x_s.

CLASSIFICATION OF EXTRACTED FEATURES USING DEEP RESIDUAL NETWORK:

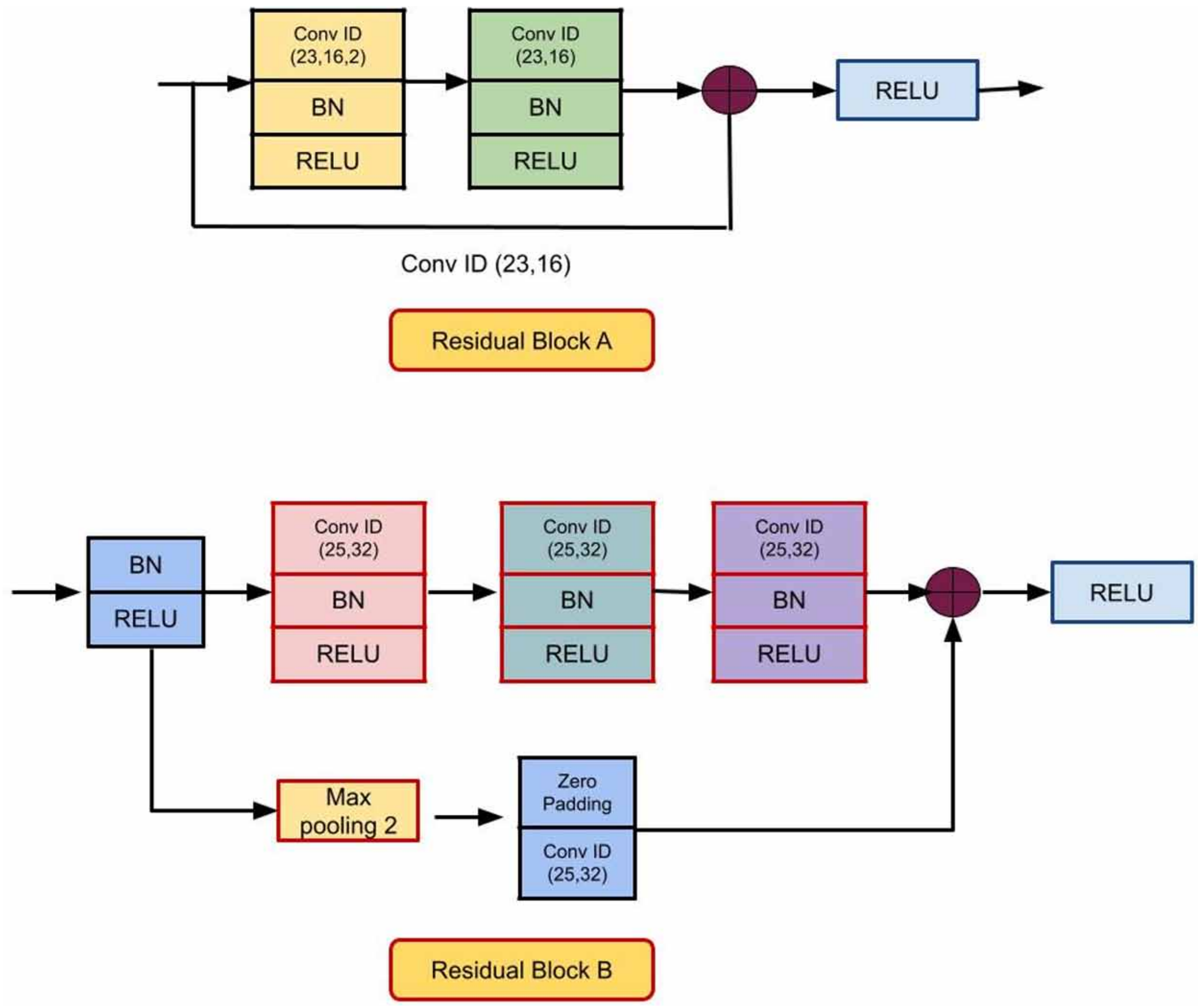
The revised deep residual network model is depicted in Figure 6 as an overview. Two enhanced residual blocks A and B, a convolutional layer with normalization and a RELU operation, a zero-padding layer with normalization and a RELU operation, a Conv layer with normalization as well as a RELU operation, a GAP layer with a Flatten and a Dropout operation, and a softMax layer are included.

Figure 6. Improved deep residual network model



This structure improves the expression capabilities of each band's features without adding to the model's complexity. Finally, nonlinearity is enhanced by utilizing RELU, a portion of negative weight values is cleared to zero, reducing computational complexity and avoiding gradient saturation and disappearance concerns. Hard downsampling, which selects element characteristics with the highest degree of activation as well as immediately contributes to classification, is comparable to residual structure B. The combination of BN, as well as RELU in this structure, can greatly increase signal propagation in the network. Max-pooling can choose elements with high activation using all of the data from feature mapping, reducing information loss and making subsequent beat categorization easier. This technique, which requires no additional parameters, creates favorable conditions for further signal feature propagation as well as improves the network's learning ability. Finally, RELU can suppress some negative weights, simplifying the network's learning process. Network can hold spatial information well and increase classification performance with a simple structure if these blocks are used.

Figure 7. Residual block A residual block B.



The input layer, convolution layer, activation function, and output layer make up the basic unit of CNN, which can be represented as Eq. (21):

$$y = f(Wx + b) \tag{21}$$

Where x is input; y is output; f is teReLU function; W is Conv matrix; b is bias.

BATCH NORMALIZATION (BN)

Input distribution of every layer varies with the parameters of the previous layer during deep network training. Internal covariant shift is the term for this phenomenon, which is commonly thought to be a significant factor determining network training speed. Batch normalization, which significantly over-comes the issue by introducing normalizing as well as shift phases in every nonlinear transformation, was developed to limit internal covariate shift induced by progressive data. Training data must first be separated into basic data units, such as mini-batch as well as then batch normalization must be performed. The methods and formulas for batch normalization for a mini-batch of size m are as follows by eq. (22):

$$\mu = \frac{1}{m}\sum_{i=1}^{m} x_i \sigma^2 = \frac{1}{m}\sum_{i=1}^{m}\left(x_i - \mu\right)^2 \tag{22}$$

$$BN_{\gamma,\beta}\left(x_i\right) = \gamma\left(\frac{x_i - \mu}{\sqrt{\sigma^2 + \varepsilon}}\right) + \beta$$

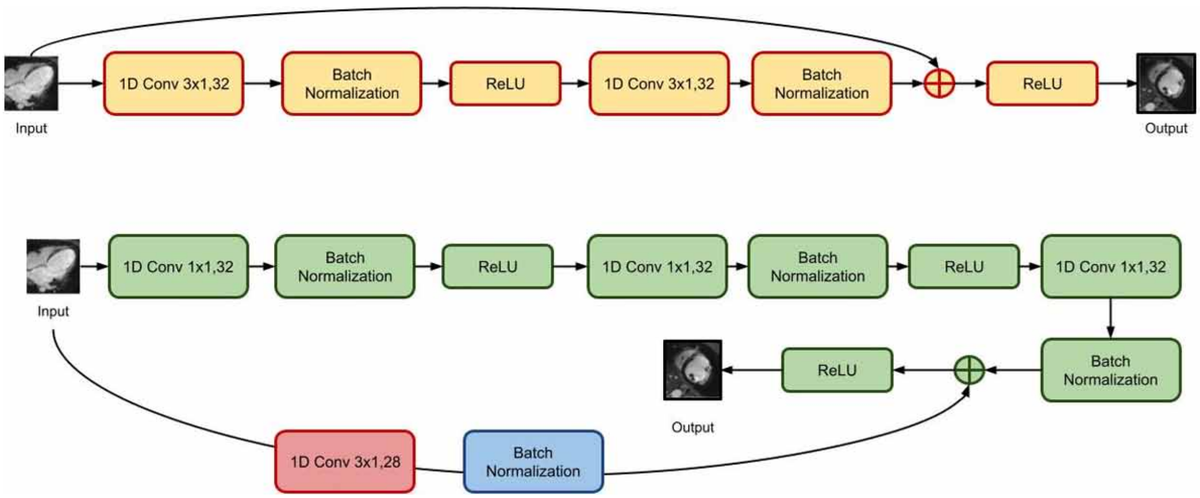
Where xi is current mini-entries, batch's and σ2 and μ are mini-standard batch's deviation and mean, respectively. ε is a numerically stable constant added to mini-batch variance, γ and β are trained parameters.

Residual Network: Because the depth of the DL network has an efficient impact on final classification as well as recognition outcomes, it is common to practice to make the NN architecture as deep as feasible. In fact, once reaching a certain depth, enhancing depth will reduce the DL network's performance. One explanation is that the more complex the network architecture, the more visible issue of vanishing/exploding gradients becomes, making network training more challenging. On the other hand, the residual network is a better DL method for CNN that avoids these issues by utilizing "shortcut connections" that bypass numerous network levels. The residual block is depicted in Figure 8 (a), and the relationship between its input and output is given as eq (23)

$$\boldsymbol{l}_j = \mathrm{ReLU}\left(\mathrm{F}\left(\boldsymbol{l}_{j-1}, \boldsymbol{w}_j\right) + \boldsymbol{l}_{j-1}\right) \tag{23}$$

Where $\boldsymbol{l}_{j-1}$ represents the current residual block's input vectors and l_j represents the current residual block's output vectors. A ReLU function activates each residual structure. The w_j is the weight parameter of the ResNet block's jth layer, which must be learned.1D convolutional, BN, and ReLU layers are included in the $\mathrm{F}\left(\boldsymbol{l}_{j-1}, \boldsymbol{w}_{\mathrm{j}}\right)$ function.

Figure 8. ResNet architectures. (a) 1D Conv residual block. (b) Proposed 1D convolutional residual block with linear projection.

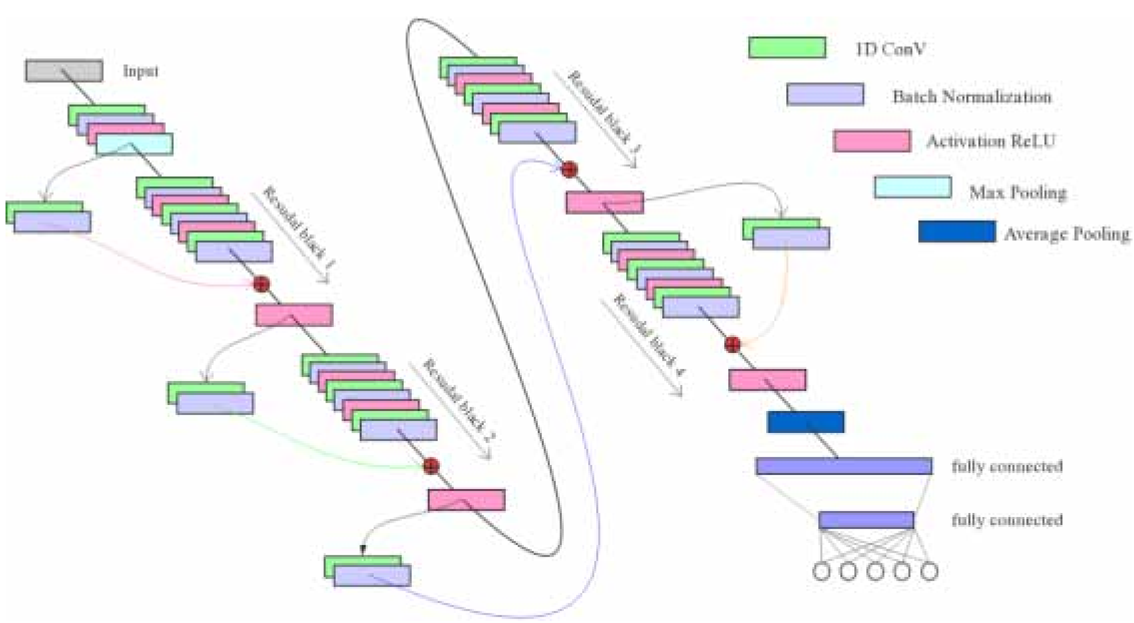


We employ linear projection Ws to match the dimensions of both $\boldsymbol{l}_{j-1}$ and F because their dimensions may differ. eq. (24) is used to define the residual structure illustrated in Fig. 8 (b):

$$\boldsymbol{l}_j = \mathrm{ReLU}\left(\mathrm{F}\left(\boldsymbol{l}_{j-1}, \boldsymbol{w}_j\right) + \boldsymbol{W}_s \boldsymbol{l}_{j-1}\right) \tag{24}$$

To complement the residual block features, we use feature maps from a 1D convolutional as well as BP layer as residual data in the shortcut connections branch.

Figure 9. Proposed ResNet model architecture



The Architecture

To efficiently learn the features of the input heart image, we propose a unique deep ResNet.The input layer of this model's network structure has 2 channels due to data from two leads. A 1D convolution, BP, ReLU, and a max-pooling layer follow the input layer. There are four residual blocks in the buried layer, each with a similar structure, as shown in Fig.9.Figure 8 depicts the design of the residual block 1.(b). First Conv layer in every residual block has a 1x1 convolution kernel, the second has a 3x1 convolution kernel, and the third has a 1x1 convolution kernel. The use of a 1*1 convolution kernel reduces the number of parameters and the amount of time it takes to compute. Softmax layer, which classifies heart disease images, is the final layer.

PERFORMANCE ANALYSIS

This project uses Keras as a DL framework, with Tensorflow as the backend. Workstation contains 8GB GPU (NVIDIA GeForce GTX -1070), Intel i7 -4790 processor (3.60GHz) and 8GB RAM.

DATASET DESCRIPTION

UCI Machine Learning Repository: Heart Disease Data Set:

Data Set Info: Even though this database has 76 features, all published studies only employ a subset of 14 of them. If the patient has a cardiac disease, the "target" field indicates that. Cleveland database, in particular, is the only one that ML researchers have used thus far. It is an integer with a value ranging from 0 to 4. Experiments with the Cleveland database have primarily focused on differentiating between presence and absence. The patients' names, as well as social security numbers, were removed from the database recently and replaced with fictitious values. One file, holding the Cleveland database, has been "processed."

Table 1. Dataset specifications

Number of attributes	75
Missing value	Yes
Number of Instances	303
Attribute characteristics	Categorical, integer, real
Associated Tasks	Classification
Data set characteristics	Multivariate
Date donated	1988-07-01
Number of web hits	1242233
Area	Life

Table 2. Dataset attributes

Attribute Name	Attribute Description	Score
cp	Chest pain type	13.55
old peak	Exercise-induced ST depression	10.90
ca	Number of vessels colored by fluoroscopy	11.70
thalach	Maximum heart rate	12.52
age	Age in years	8.60
thal	Thallium scan	10.28
trestbps	Blood pressure at rest	7.46
exang	Exercise-induced angina	5.89
chol	Serum cholesterol	7.78
gender	depression	3.35
slope	Slope of the peak in exercise-induced ST	4.95
fbs	ECG results at rest	0.98
restecg	Gender	2.04

Framingham Heart Study dataset results from an ongoing cohort study in Framingham, Massachusetts. It has 15 columns and roughly 4200 rows of data and is freely accessible on the Kaggle website. Each column represents a potential risk factor, whereas every row represents a person's behavioral, demographic, and medical data. The Faisalabad Institute dataset contains 299 heart failure patients' records from the Faisalabad Institute of Cardiology and Hospital in Faisalabad, Pakistan, and is based on 13 attributes and one class. The dataset is available for public use on the Kaggle website. Finally, South African Hearth dataset contains 462 patient records and 13 variables that can be used to predict mortality from HD. The dataset is available on the KEEL website to the general public.

Table 3. Dataset description

Dataset	Number of Records	Number of Attributes	Prediction/Diagnosis
Faisalabad Institute	299	13+ Class	Prediction/Diagnosis
Cleveland	303	13+ Class	Prediction/Diagnosis
Framingham	3658	15+ Class	Prediction
South African Hearth dataset	462	9+ Class	Prediction

Table 4. Comparative analysis of accuracy

Number of Epochs	MLA	LSTM	GAN_DRN
100	60	69	72
200	65	75	80
300	69	79	85
400	72	85	90
500	75	86	96

Figure 10. Comparative analysis of accuracy

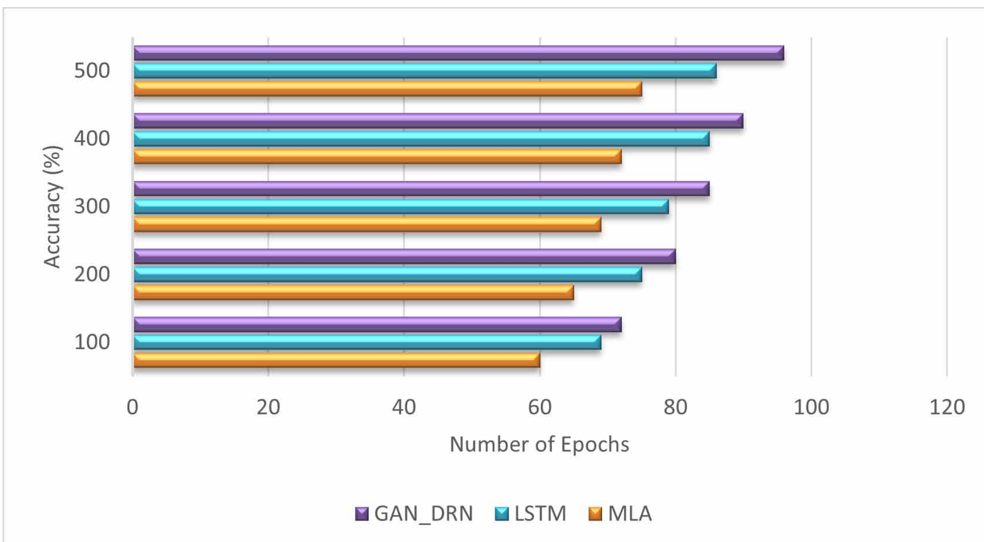


Table 5. Comparative analysis of precision

Number of Epochs	MLA	LSTM	GAN_DRN
100	55	61	72
200	59	65	75
300	61	69	79
400	65	72	81
500	67	75	85

Figure 11. Comparative analysis of precision

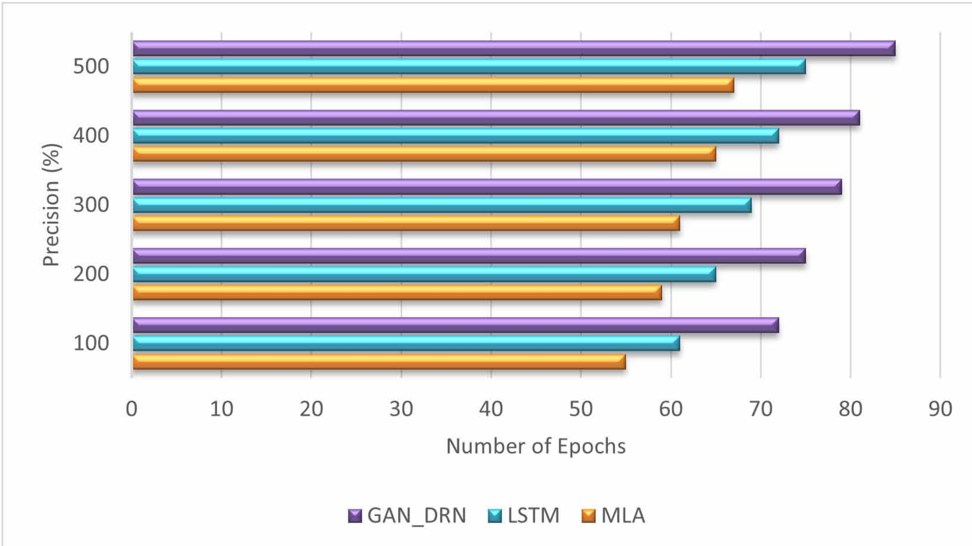


Table 6. Comparative analysis of recall

Number of Epochs	MLA	LSTM	GAN_DRN
100	61	65	71
200	65	69	73
300	69	72	75
400	71	75	79
500	73	79	80

Figure 12. Comparative analysis of recall

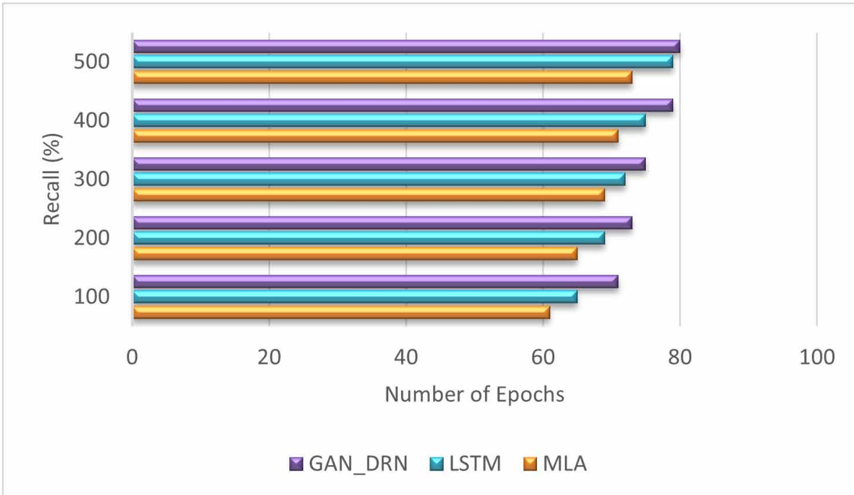


Table 7. Comparative analysis of F1_Score

Number of Epochs	MLA	LSTM	GAN_DRN
100	50	55	61
200	53	59	63
300	55	61	65
400	59	63	69
500	60	65	71

Figure 13. Comparative analysis of F-1 Score

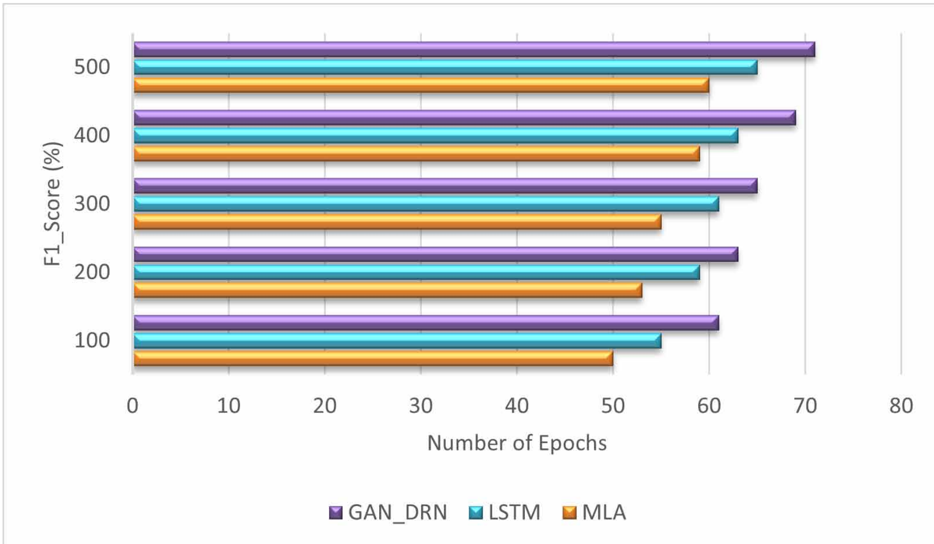
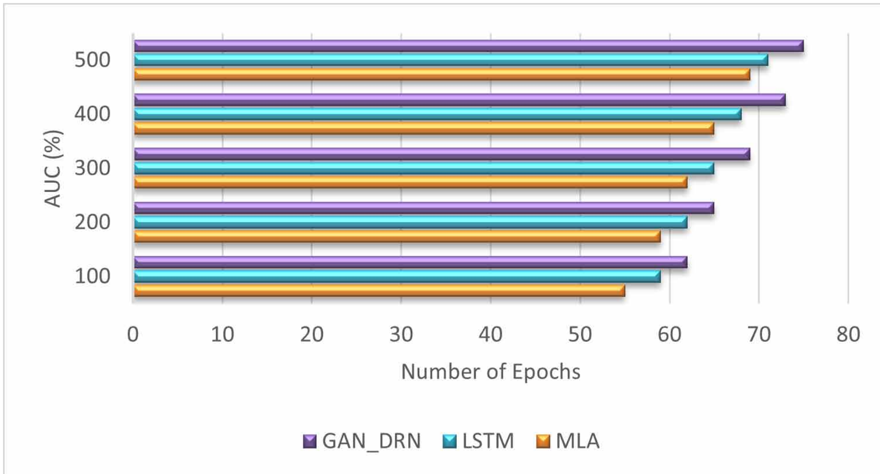


Table 8. Comparative analysis of AUC

Number of Epochs	MLA	LSTM	GAN_DRN
100	55	59	62
200	59	62	65
300	62	65	69
400	65	68	73
500	69	71	75

Figure 14. Comparative analysis of AUC



The above table 4-8 and figure 10-14 shows a comparative analysis of accuracy, precision, recall, F-1 score, and AUC between the proposed and existing technique. Here the accuracy obtained by proposed GAN_DRN is 96%; existing LSTM attained 86% and MLA is 75%, where precision obtained by proposed GAN_DRN is 85%, existing LSTM obtained 75% and MLA is 67%; recall obtained by proposed GAN_DRN is 80%, LSTM is 79% and MLA is 73%; F-1 score attained by proposed GAN_DRN is 71%, LSTM is 65%, MLA is 60%; AUC attained by proposed GAN_DRN is 75%, LSTM is 71%, MLA is 69% by existing technique. From the above analysis, the proposed technique obtained optimal results in cardiac disease detection.

Wearable devices are currently being employed for a variety of health monitoring applications. The sensor is one of the most crucial components of data collecting. With advancements in semiconductor technology in recent years, sensors have brought a wide range of parameters closer to realization. The ability to use a gadget in the actual world, performance, efficiency, and power consumption is the most essential criteria in this study. We also took into account the cost of each item. This project provides the user with two main features: First, an Android software that uses Bluetooth to interface with a wearable gadget that measures heart rate. When the user's BPM becomes unstable, the app sends SMS notifications to a medical expert's phone, a patient's family member's phone, or their relatives, providing the user's present location and patient state. Second, an Android/desktop application that determines whether or not a user has heart illness with a single click, using an ML module to evaluate user data and diagnose HD. Other capabilities include evaluating daily steps and verifying the location of nearby hospitals, heart centers, health centers, and users. To do so, using Java programming language, Python programming language, and C programming language. Embedded C programming language is utilized to design embedded devices with Eclipse IDE, which makes the development process easier. With Android Studio 3, which includes a large number of libraries, Java programming is utilized to create Android apps. The desktop app was created using the Python programming language and the Anaconda Jupyter notebook. ML and DL models are also included. They've all visited a number of important libraries. The benefits of the system given to the user determine the project.

CONCLUSION

This chapter proposes a novel technique for the detection of cardiac disease using feature extraction and classification based on deep learning techniques. Here the input data has been collected based on wearable device collected data with the IoT module. This data has been pre-processed using adaptive histogram normalization and segmented the image based on the threshold method using Ostu thresholding technique. The segmented image feature has been extracted using a generative adversarial network and the classification of extracted features using a Deep Residual Network. The experimental analysis was obtained by the proposed GAN_DRN in terms of accuracy was 96%, precision of 85%, recall of 80%, F-1 score of 71%, and AUC of 75%.

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Chapter 10
PPG-Based Cardiovascular Disease Predictor Using Artificial Intelligence

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ABSTRACT

Heart disease is estimated to be the major cause of death among the middle-aged population worldwide. Researchers assess huge volumes of medical data using a variety of statistical, machine learning, and deep learning methods, supporting healthcare practitioners in predicting heart illness. This work aims to predict the likelihood of people developing heart disease using a wearable wristband that can record photoplethysmography (PPG) signals. Cardiovascular features extracted from the PPG signal are used to train the prediction algorithm. It enables the patient to self-monitor their health and take precautionary measures and treatment at the onset of symptoms of the disease. Random forest, convolutional neural network, long short-term memory networks are trained using publicly available databases comprising both affected and standard parameters and thereby used for comparison with the acquired sensor data for predictive analysis.

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1 INTRODUCTION

Cardiovascular Disease (CVD) is a term that refers to a range of conditions that have an impact on the heart (Afilalo et al., 2009). They include lack of fitness, high cholesterol, hypertension, etc. An improper diet, harmful alcohol consumption, and excessive sugar levels are all factors that contribute to heart disease (Amin et al., 2013). Identifying and treating the people who are at risk of CVD is highly essential in order to reduce early deaths. Hence to prevent early death, an early and accurate medical diagnosis of heart disease must be made (https://appa.who.int/iris/handle/10665/43685). Lack of adequate medical datasets, lack of flexibility in selecting features, and lack of implementation of proper predictive algorithms are all obstacles that delay effective heart disease prediction (Sharma et al., 2020).

Males are more likely than females to get a CVD. It is twice as likely for males to develop heart disease during their lifetime as for females. The increased risk continued even when traditional heart disease risk factors such as lipid disorders, hypertension, insulin disorders, body mass index (BMI), and fitness activity were taken into account (Ebrahim et al., 1999). The factors that contribute to these differences in cardiac illness and mortality rates are numerous. Differential access and poor quality of health care, environmental or neighborhood impacts, persisting racial prejudice, health actions including nutrition, smoking, socioeconomic position, and genetic variation have all been proposed as factors contributing to congestive heart failure (Anderson et al., 1991).

ML and DL are examples of artificial intelligence approaches that can help with early screening and diagnosis of CVD at an early stage, in addition to prognosis evaluation and outcome prediction. With the proliferation of electronic health records (EHR), enormous amounts of quantitative, qualitative, and transactional data have been collected. With the use of clinically relevant information revealed in huge amounts of data, AI approaches can also assist clinicians in making the best clinical resolution, enabling prior diagnosis of subclinical organ dysfunction and therefore improving the quality and efficiency of cardiac healthcare (Faizal et al., 2021). A system based on such risk factors would not only assist medical experts and doctors but also alert patients to the possibility of CVD before they visit a medical center or undergo expensive medical examinations (Ebrahim et al., 1999). As a result, employing suitable classifier algorithms, this research proposes a technique for predicting heart disease using major risk variables. LSTM, CNN, and RF methods are among the major classification algorithms applied in this technique for analyzing whether patients have CVD or not.

In healthcare, machine learning and deep learning have shown effective assistance in assisting with decision-making and predicting from large datasets (Mohan et al., 2019). The machine learning disease prediction system uses information provided by users to identify diseases. Information entered into the web system predicts a patient's disease or the user's symptoms and gives results based on the information given. With its combination of ML and artificial intelligence, DL can be thought of as a means of simulating how humans acquire different types of knowledge. With the computer-aided diagnosis, this field relies on its own ability to learn and improve (Swathy & Saruladha, 2022).

ML is a data analytics approach that automates the building of analytical models. In this branch of artificial intelligence, systems learn from data, recognize the design, and make a conclusion without human interference (Sardar et al., 2019). Supervised machine learning is the type of machine learning where the model is trained based on previous data to make future predictions (Kotsiantis et al., 2007). A deep learning approach can be used to predict a disease based on collected data (Ali et al., 2020). Finding hidden information in a dataset, followed by the ability to apply that knowledge to others, is what it is all about (Kotu & Deshpande, 2o14). Many ways exist within the deep learning methodologies for transforming a large dataset into meaningful information (Vaswani et al., 2017). This method can be used for knowledge discovery, application, and prediction based on knowledge. The forecast is primarily reliant on the data that has been trained. The dataset can be trained using the back-propagation method by using an Artificial Neural Network (ANN). It is made with a multilayer perceptron, which is a fundamental processing unit that can handle non-linear problems while a single perceptron can only tackle linear ones (Suvkens et al., 1995).

It is crucial to complete the diagnosis as soon as possible. Usually, this is done with the assistance of a doctor. Patients will typically receive disappointing results with high medical costs (Ponikowski et al., 2014). As a result, an automated medical diagnosis and prediction system would be tremendously beneficial. To compare prediction models, public datasets on heart diseases are accessible (Abukhousa & Campbell, 2012). The development of machine learning and deep learning allows academicians to create the best prediction models possible by utilizing enormous databases (Bharti et al., 2021). A system-based risk factor would benefit medical professionals as well as patients because it would alert them about potential CVD symptoms even before they visit the hospital or undergo costly medical testing (Larroza et al., 2017). Table 1 showcases the summary of research work pertaining to CVD prediction with the focus on signals and signals source used, features extracted and various classifiers used.

2 SUMMARIES OF PREVIOUS RESEARCH

Globally, CVD has been the leading cause of death in the last decade. In India, the incidence of CVD is expected to increase from 2.27 million in 1995 to 4.8 million in 2022 Over the past several decades, CVD occurrence rates in India have increased from 1.6% to 7.4% among rural populations and from 1.5% to 13.7% among metropolitan populations (Mozaffarian et al., 2016).

Table 1. Summary of related research work

S. No	Author & Year	Signal used & Signal Source	Features Extracted	Classifier Used
1.	**Apurb et al., 2020**	PPG, ECG	Fingertip PPG and Electrocardiogram (ECG) signals are processed based on the phase and amplitude for monitoring continuous systolic and diastolic blood pressure.	Aggregation network-based deep learning
2.	**Alaa et al., 2019**	PPG	Peak-to-Peak Time, Crest Time, and Maximum Slope were found to be vital features for accurate classification	Kernel
3.	**Zaibunnisa et al., 2021**	ECG	Framingham Risk Score.	K neighbor classifier, Support Vector Machine classifier (SVM), Decision Tree classifier
4.	**Galla et al., 2020**	Statistical data Different geographical areas (Hospital)	The fuzzy-based model was used to retrieve real-time patient data.	ANN, Decision Tree, SVM, and Naïve Bayes
5.	**Bharti et.al., 2021**	Public Health Dataset	Peak and thali distribution were found to be featured for accurate classification	K Neighbors classifiers, Random Forest, SVM, Decision Tree
6.	**Abdel et al., 2020**	PCG	Using the spectral density plots, phonocardiogram signals can be generated.	Radial Basis Function (RBF) network and Back-Propagation Network (BPN) techniques
7.	**Fu et al., 2020**	ECG	Long ECG recordings (QRS complexes), Short ECG recordings (P and T wave)	AI algorithms such as CNN and Recurrent Neural Network (RNN).
8.	**Shah et al., 2020**	ECG	A classification analysis of ECG using QRS complexes.	Continuous Wavelet Transform (CWT) and SVM.
9.	**Devansh et al., 2020**	Cleveland database	The UCI repository of the heart patient was conducted through the WEKA tool.	K neighbor classifier, Naive Bayes, Decision tree, and RF algorithm
10.	**Krittanawong et al., 2017**	ECG	To investigate novel genotypes and phenotypes in known diseases, AI approaches are used.	Algorithms include ANN, SVM, Decision Tree, Random Forest, Naive Bayes, and KNN.
11.	**Josep et al., 2012**	Echo-cardiography	Heart rate, respiratory rate, SPO_2, blood pressure.	Kaplan Meier event-free survival analysis.
12.	**Mohammed et al., 2011**	PPG	Maximum Slope, Heart rate, SPO_2.	Artificial Neural Network approaches that classify a PPG signal into two distinct classes i.e., Network-based on Multi-Layer Perceptron (MLP) with back-propagation strategy and Gaussian Mixture Model (GMM).

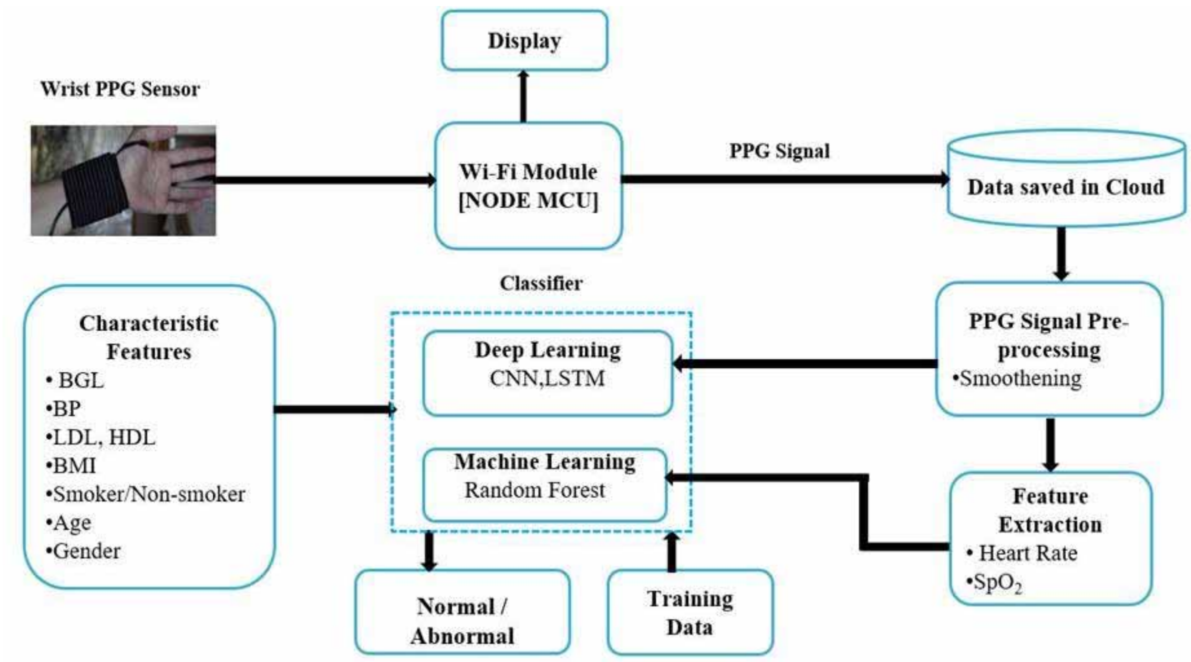
3 METHODOLOGY

In the proposed model, a wearable wristband is designed to acquire PPG signals from individuals, and the signal is saved in the cloud through a Wi-Fi module. The signal can be imported from the cloud, after which preprocessing steps are performed using a smoothing filter. Few feature extraction algorithms are utilized to extract the features relevant to the CVD, and the extracted features are also given to the classifier. The block diagram of the proposed work is depicted in figure 1. The developed wearable wristband with an automated screening system that can predict CVD using PPG signals is shown in figure 2. Appropriate signal processing algorithms have been implemented to extract relevant features that support the prediction of cardiovascular disease. The following classifiers are used for classification and their performance has been analyzed.

- Random Forest
- Convolution Neural Network
- Long-Short Term Memory Network

The non-invasive approach makes use of a simple light source and a photodetector with which the model monitors the volumetric fluctuations of blood circulation to acquire the PPG signal. As a result, small overall solution size is achieved without compromising optical or electrical performance. The external hardware components are integrated into the wearable wristband. File Input File Output (FIFO) allows the sensor to connect to a microcontroller on a shared bus that does not continuously read data from registers. The acquired signals are given to the cloud using a Wi-Fi module. The microcontroller unit has been designed for wearable electronics to achieve the lowest power consumption possible with several proprietary techniques. The Espressif System Smart Connectivity Platform (ESCP) is often designed for minimal space requirements. It has an embedded Wi-Fi capability that can be added to any microcontroller-based system with simple connectivity through the Universal Asynchronous Receiver-Transmitter interface. It operates at a 2.4 GHz frequency, corresponding to 0.125 meters of wavelength. It employs a 32-bit RISC (Reduced Instruction Set Computer) Central Processing Unit. The Arduino AT mega is an advanced virtual RISC microcontroller. The Arduino ATmega-328 is an 8-bit microcontroller and it operates in the range of 3.3V to 5.5V. It can execute many instructions in a single clock cycle and provide almost 20 MIPS (million instructions per second) at 20MHz. It has a high performance and low power design. It covers 32kb of programmable Flash, 1kb of EEPROM, and 2kb of SRAM (Static Random Access Memory). It can perform all the general-purpose tasks on a single machine, like a computer. The devices in the series are precision temperature devices for integrated circuits. Its output voltage is directly proportional to the temperature in degrees Celsius. Therefore, the sensor is calibrated directly to Celsius. No external calibration or trimming is required to achieve normal accuracy. It features low output impedance, a linear output, and precise and unique calibration that facilitates interface with the reader or control circuitry. It requires a power of 60μA and operates at temperatures between -55^0 C and 150^0 C. Organic Light-Emitting Diode (OLED) is a relatively new technology that uses light-emitting diodes where light is produced by organic molecules and could replace today's LCDs and LEDs. The display format is about 128×64 dots. OLED displays emit visible light because they work without a backlight. It can be embedded in textiles and clothing and offers a higher contrast ratio and wider viewing angle than LCDs. It also has much faster response times than LCDs. The Thing Speak server is an open data platform for the Internet of Things that can collect store, analyze, visualize, and manipulate data from sensors.

Figure 1. Block diagram of CVD predictor



3.1 Pre-Processing

Signal preprocessing focuses on analyzing, altering, and synthesizing signals such as sounds, images, and scientific measurements. This technique can be used to upgrade the transmission, storage viability, and subjective quality and to also detect the components of interest in a measured signal. Preprocessing is a stage that includes artifact removal, denoising, and resampling the signal to comply with detector input specifications. The preprocessing module can be divided into three components:

i. **Extraction** involves the process of extracting important data from multiple homogeneous or heterogeneous data sources.
ii. **Conversion** refers to the cleaning and manipulation of data to convert it to the proper format.
iii. **A load** is the insertion of the transformed data into the memory of the processing unit that processes the training data.

Applying an appropriate filter to the signal is necessary in order to remove the artifacts and spurious noise added to the signal. Smoothing the data removes random variation, and they show a typical trend and cyclic components. Smoothening is achieved using the moving average filter in this method. Machine Learning and Deep Learning algorithms work well when the data is introduced in a format that emphasizes the relevant aspects needed to solve the problem. Feature extraction practices, including, data transformation, data reduction, data wrangling, feature selection, and feature scaling, help reconstruct raw data into a format suitable for a particular type of algorithm. This can significantly decrease the processing power and time required for training and guessing new machine learning and AI algorithms.

3.1.1 *Moving Average Filter*

As its name suggests, it is a low-pass FIR (Finite Impulse Response) filter that is frequently used to smooth out data or signal arrays. It takes n number of samples at a time and works by summing those samples to produce a single output point. Cycles of long-term trends can be identified through moving averages, which can resolve short-term fluctuations. Based on the application, there may be a difference between short-term and long-term moving averages, which will be reflected in the moving average variable. A moving average is a statistical technique that filters out higher frequency elements of non-time series data without relating them to time in any particular way. But it usually does imply a certain order. In this case, the structure of the Low Pass Filter is very transparent to filter out undesirable noise from the intended data. The smoothness of the output increases with magnitude (the parameter L), while as the data becomes increasingly blunt, sharp transitions become less apparent. Moving average filters possess the following characteristics: an excellent time-domain response but, an insufficient frequency response. There are three main functions of the moving average filter:

i. Using L input points, an average is calculated for those points by the filter, which produces an output value.
ii. As a result of complex computations, the filter introduces a significant delay.
iii. Low-pass filtering (with excellent response in the time domain but a weak response in the frequency domain). For an L-point discrete-time moving average filter, the difference equation is given in Equation 1, where x is the input vector, and y is the average output vector.

$$y[n] = \frac{1}{L}\sum_{k=0}^{L-1} x[n-k] \tag{1}$$

As shown by the frequency response, the roll-off is extremely slow, and the attenuation in the stopband is not adequate. Considering the attenuation, the stopband is very weak. The moving average filter is unable to split one frequency band from another. When good performance is measured in the time domain, it is weakly measured in the frequency domain. Despite their excellent smoothing capabilities (effects appear in the time domain), moving averages are very destitute low-pass filters (effects are seen in the frequency domain). Noise reduction can be achieved by adding a few adders and delay elements. With low-pass filtering, the capacity to suppress the stopband sidelobes and to achieve an excellent frequency domain response is less important than basic filtering ability, which is where moving average filters are most useful. The main assumption of regression models utilizing moving averages is that the independent error terms are undetectable and the parameters are estimated by the weight.

3.2 Feature Extraction

The technique involves computing preselected characteristics of a PPG signal, which are then fed to a final processing scheme such as a classifier, to aid in CVD prediction using PPG-based systems. In the following step, vital feature points are extracted from the PPG signal by using differential thresholds. Three steps are involved in this method: interpolation, differentiation, and determination of extreme points.

Our goal is to create new features from existing ones in the dataset, which will reduce the number of features in the dataset. It also helps to reduce the amount of redundant data in the data set. Characteristic features extracted from the individuals are listed in table 2.

Table 2. Characteristics and details of cardiovascular disease

S. No	Characteristic	Details
1.	Age	Age of patient in years
2.	Gender	0 =Male; 1=Female
3.	Smoking condition	0 = Non-Smoker; 1 = Smoker
4.	Height	Height of the patient in Centimeter (cm)
5.	Weight	Weight of the patient in Kilogram (kg)
6.	Hypertension	Diastolic and systolic blood pressure at rest (in mm/Hg)
7.	Blood Glucose Level	Fasting blood sugar levels are above 120 mg/dL. Less than 100 mg/dL (5.6 mmol/L) is normal and 100-125 mg/dL (5.6-6.9 mmol/L) is considered prediabetes.
8.	Cholesterol	Serum cholesterol (0 = Normal range, 1 = High cholesterol level)
9.	Cardiac arrest	There are four types of cardiac arrest: angina pectoris, atypical angina, non-anginal pain, and asymptomatic.
10.	Temperature	Temperature is acquired through the sensor (varies according to the patient)
11.	Heart Rate	Maximum heart rate achieved
12.	SPO_2	Maximum oxygen saturation is achieved through the PPG signal.
13.	Target	Predicted Outcomes = Normal, Disease_ Risk

3.3 Database

Data that is needed for forecasting is obtained from open sources. Collecting data is an important step because the quality and quantity of the data directly determine the success of the proposed model. A common approach is to get data from open sources such as Kaggle (https://www.kaggle.com/datasets). Kaggle is a data science community with tools and resources, including externally sourced artificial intelligence. This is a technique for assessing and sharing the performance of ML and DL algorithms. It can be used for regression problems and supervised learning algorithms. This step takes one record and divides it into two subsets.

In this proposed model, the data is separated into the training data being 80% and the test data being 20%. First, there is the training data, which is used to fit the model and is referred to as the training dataset. We don't use the second subset to train the model, but instead provide the input element from the dataset to the model, which makes a prediction and compares it to the expected value. Using the model file, the second dataset is referred to as the test dataset. Here using the model file, certain types of patterns can be recognized. Training data is sent to the classification algorithm. After training, the classification algorithm will produce the expected outcomes. When it comes to predicting or classifying a problem, the distribution of the data is crucial. We can observe that heart illness is identified 54.46 times in the dataset, while no heart disease occurred 45.54 times. As a result, we must balance the dataset to avoid overfitting.

Figure 2. Designed wearable wristband

3.4 Random Forest

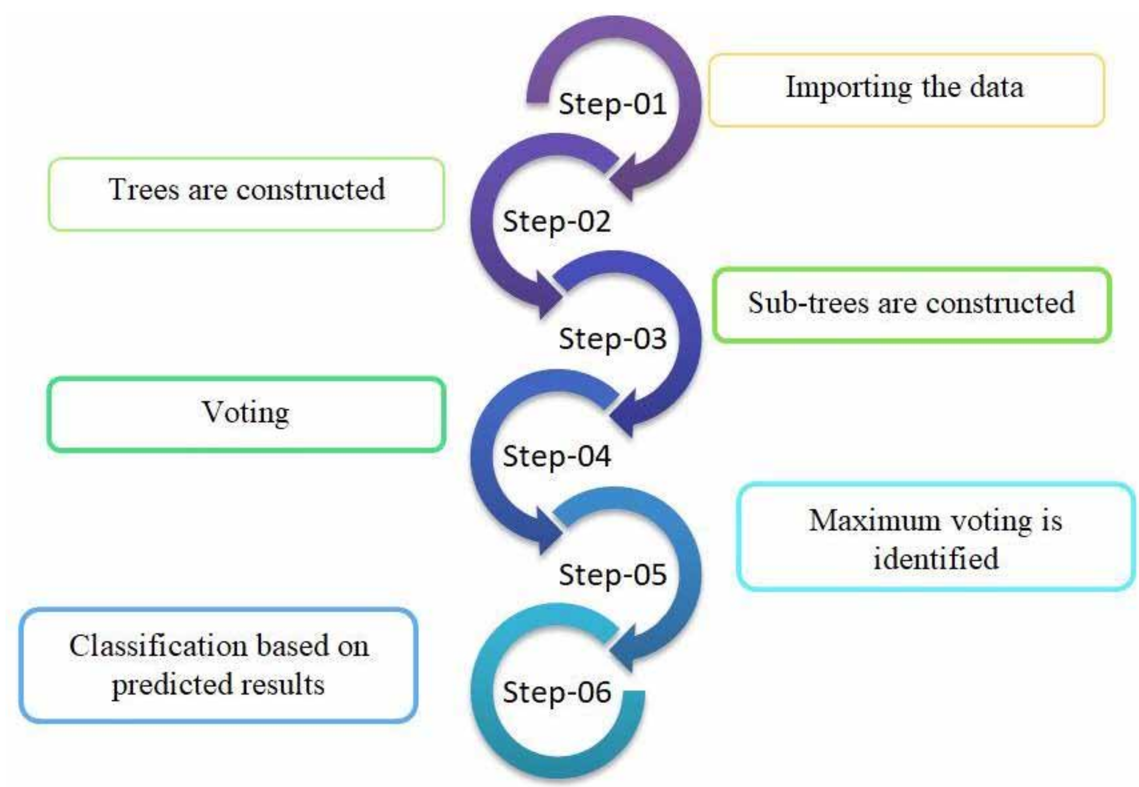
An RF is a classifier that consists of multiple decision trees for different subsets of a given data set that uses the mean to better predict the accuracy of that data set. The building blocks of RF algorithms are decision trees. RF is a popular machine learning algorithm related to direct learning techniques. The more trees there are in the forest, the greater the accuracy and the avoidance of overfitting problems. It can also maintain accuracy even when most of the data is missing. This algorithm can be used to determine disease propensity and disease risk. As a result, doctors can judge a patient's reaction to a particular drug. An RF algorithm consists of a series of decision trees, where each tree in the ensemble consists of data samples taken from training samples with replacements called initial samples, as shown in figure 3.

A method for predicting heart disease has been proposed by using this classifier that results in 84% accuracy. Cardiovascular disease is predicted using ensemble learning approaches. The proposed methodology entailed combining the different deep learning algorithms with the RF, a machine learning technique that is used to evaluate the CVD. Artery blockage denotes the existence of cardiac risk. Many researchers are working in this field to develop software that can assist doctors in making decisions regarding the prediction and diagnosis of heart disease (Romiti et al., 2020). In this proposed model, data mining techniques can be used to predict cardiovascular disease in advance, allowing patients to receive appropriate treatment. Here, the different algorithms are used for comparative analysis, but the prediction accuracy of the RF algorithm is the lowest. Based on the algorithm, sensitivity is 85.67%, specificity is 52.38%, and accuracy is 84.76%.

The classification in RF uses an aggregate method to achieve the results. After training, averaging the predictions from all the separate regression trees can be used to make predictions for unseen samples. Seventy-eight regression trees were formed approximately. By default, for every 500 datasets, 10 regression trees are formed. Then the sub-categories or subtrees are formed. It can be of two types in this proposed model. Our decision tree uses continuous variables. A continuous variable decision tree has a continuous target variable and is known as a continuous variable decision tree. There is a linear relationship between the predictor variables and the target variables, so the basic learner is just as accurate as the ensemble learner. This classifier is used to diagnose patients by assessing their previous medical history. In comparison to the decision tree algorithm, it is more accurate in predicting the outcomes of thousands of input variables that can be processed without deleting them. This works in four steps.

i. Choose a random sample from a particular dataset.
ii. Create a decision tree for each sample data set and get the prediction output from each decision tree.
iii. Vote for each expected result.
iv. As the final prediction, select the output result with the most votes.

Figure 3. Data flow in random forest



3.5 Convolutional Neural Network

The Artificial Neural Network (ANN) is made up of interrelated nodes that function similarly to real neurons in that they receive, process, and output data. Nodes in any artificial neural network can be classified in three ways: input nodes, hidden nodes, and output nodes. As with sensory neurons in the central nervous system, input nodes function similarly, bringing a data set to processing. The details from the data set are processed by hidden nodes, and the last elucidation of the data is represented by output nodes. Convolutional neural networks are a type of artificial neural network that "learns". This can happen through a variety of mechanisms, such as backpropagation (Krittanawong et al., 2017). The most commonly used model type in Python programming is the successive type. It is the easiest method to create a CNN model. This allows us to build the model layer by layer. The term "convolution" in CNN refers to the mathematical function of convolution. A linear operation multiplies two functions to produce a third function that shows how one function changes the shape of the other. Convolutional neural networks (CNNs) indicate that networks use a mathematical operation called convolution. A convolutional neural network (CNN) consists of an input layer, a convolution layer, a pooling layer, and an output layer. CNN's biggest advantage over previous models is that it automatically discovers important features without human control (Nasrabadi & Haddadnia, 2016).

The Convolutional Neural Network method uses structured data to determine early heart disease risk. Our model's accuracy is 95.35%, with a sensitivity of 99.18% and a specificity of 31.36%. In the future, the work will be to expand our algorithm to include unstructured data as well. Medical specialists have approved all of the quality and laboratory tests that have been considered so far. Both organized and unstructured data can be utilized with the CNN algorithm. Images can also be used in conjunction with CNN algorithms to forecast certain diseases. The reason for this is that it employed a very good optimization strategy to improve the CNN algorithm's accuracy. CNN is a kind of deep neural network (DNN) with a spectral layer that specifically learns lower and higher-level features. CNN is a useful model for predicting statistics, modeling, and other tasks. Simply put, it outperforms CNNs thanks to three additional concepts: local filters, max-pooling, and weight sharing. Figure 4 shows the architecture of CNN, which is used to predict cardiac disease. To extract important features, the CNN is composed of a few pairs of convolutions and pooling layers. The convolutional layer always comes after the pooling layer. Pooling is commonly used in the frequency domain. For the problem of variability, max-pooling produces good results. The highest filter activation from different points within a particular window is collected by a layer called a max-pooling layer. At this stage, the convolution features are created at a lower resolution. The max-pooling layer allows the architecture to tolerate tiny changes in the placement of the pieces of the object, resulting in faster convergence. On the other hand, fully connected layers aggregate the inputs from all points into a 1-D feature vector. The overall inputs are then classified using the SoftMax activation function layer. The CNN architecture consists of two main parts:

i. A convolution tool that splits and identifies various features of a dataset for scanning in a process called feature extraction,
ii. An integrated layer that uses the convolution process output to predict the class of a dataset using the features extracted previously.

Input Layer: The foremost layer is called the input layer. The input layer of the neural network contains artificial input neurons, which then send the output data to the system for further processing.

This layer transfers data directly to the next layer. The next layer is the first hidden layer, where the data is accumulated by the first hidden layer.

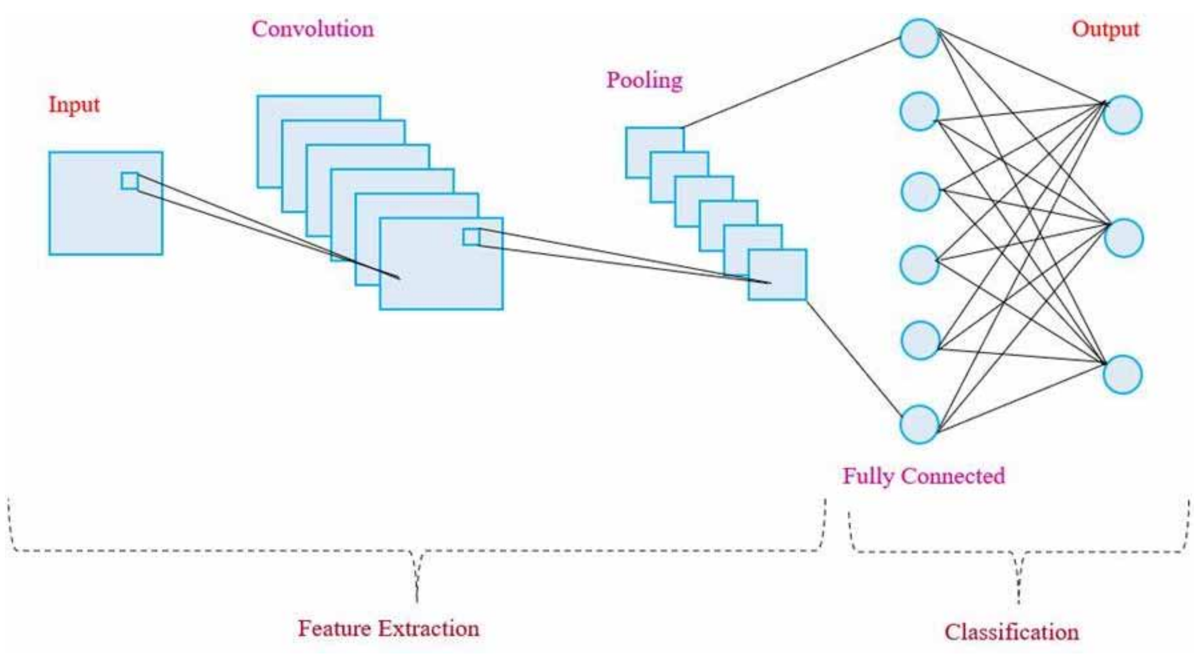
Convolutional Layer: The convolutional layer is the basic structure of a CNN where most of the computations are performed. Convolution is the first layer that extracts features from the input training data, also known as a convolution matrix or convolution mask. It consists of a digital filter that analyses the input data using convolution. The result of the convolution operation is passed to the second layer as the convolution layer proceeds to perform the convolution on the input data. Convolution converts every pixel in the received field to a single value.

Pooling Layer: In addition to their parametric reduction, pooling is the layer added after convolution. Pooling layers are neither necessary nor sufficient for proper deformation stability in CNN algorithms. Pooling layers help control overfitting by gradually reducing the size of the view, reducing the number of parameters, and reducing the amount of memory.

Dense Layer: A densely connected layer consists of multiple layers connected by weight matrices and multiplexed input data by each layer's weight matrix. Also known as the "line layer" this layer connects each input neuron to each output neuron. The output of the convolutional layer represents the high-level features of the data.

The architecture of the CNN model is represented in figure 4.

Figure 4. Data flow in Convolutional Neural Network



3.6 LSTM

In the discipline of DL, LSTMs are artificial recurrent neural networks (RNNs) that can learn sequence dependencies in sequence prediction problems and are designed to overcome the problem of backflow of errors. LSTMs are designed to work differently from CNNs because LSTMs are typically used to process and predict a given sequence of data (Jasmin et al., 2016). It is widely used for sequence prediction problems and has proven to be very effective. An LSTM network was used to accurately classify auricular fibrillation (A-Fib) in a variety of electrocardiography, echocardiography, or plethysmography data. It achieved 99 percent accuracy. Using LSTM models, structural heart distortion threats were also automatically identified from digital phonocardiogram (PCG) signals for use in congenital heart disease screening applications. Additionally, it has been demonstrated that a bi-directional neural network architecture built by utilizing the Bi-LSTM-Attention method increases the accuracy of cardiovascular disease applications (accuracy of 98.49 percent) above the literature review. Deep learning applications have also been reported for medical imaging, where futuristic results have been achieved, and neural networks have worked well for many challenging situations in biomedicine.

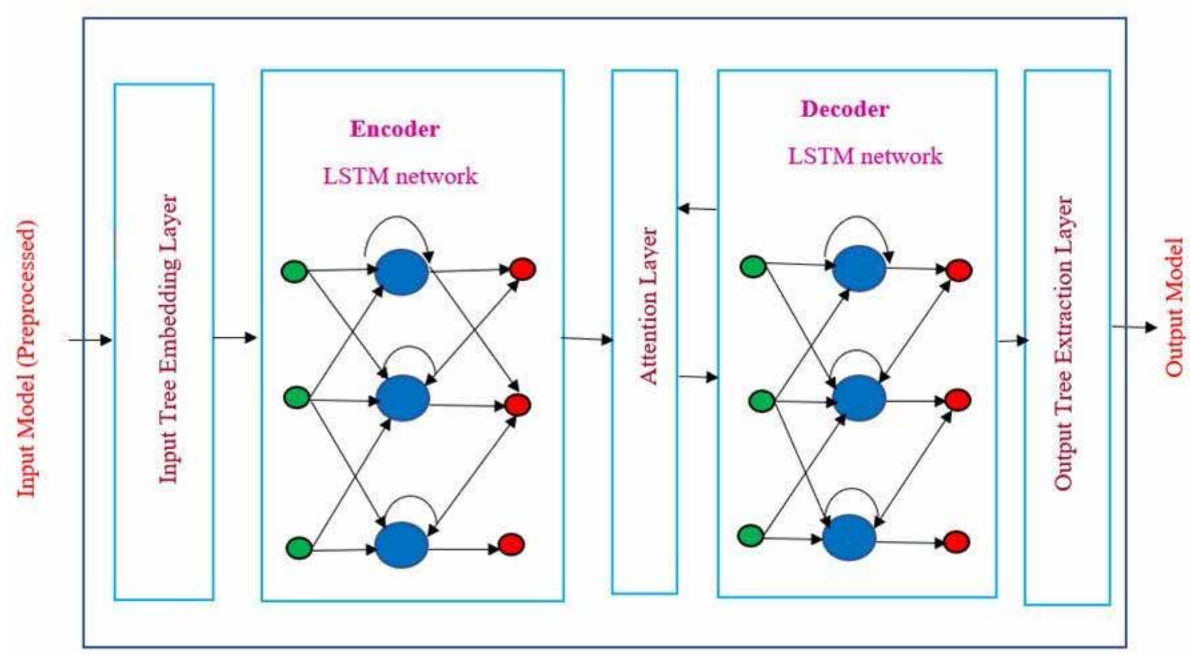
Prior strong prediction models struggled to deal with data spanning multiple periods with different intervals, and handling large volumes of patient hospital records was ineffective in improving forecast accuracy. The goal of this research is to use enhanced LSTM models to predict cardiovascular disease. To predict cardiovascular disease, in an attempt to improve the standard LSTM, a new model and architecture were suggested as shown in figure 5. To overcome the prediction time limit vector obtained by smoothing an irregular period imposed by an irregular time interval, which is then fed into the forgetting gate of the LSTM, we can keep important information from the past and forget about unnecessary information. Information is stored in cells, and memory manipulation is performed by three gates:

Forget Gate: The conditional determination of which information should be discarded from a block.
Input Gate: The memory state is updated conditionally based on which input value was provided.
Output Gate: Input and block memory are taken into consideration when deciding what to output.

It is used for processing, forecasting, and classification based on time series data. It provides a wide range of learning rates, input, and output bias parameters. The main advantage is that the complexity of each weight update is reduced to 0(1) by LSTM, similar to backpropagation in time (BPTT). LSTMs have recently gained popularity because they can solve the problem of dissipating gradients (Krittanawong et al., 2020).

The architectural structure of the LSTM network is represented in Figure 5.

Figure 5. Dataflow in Long Short-Term Memory Network



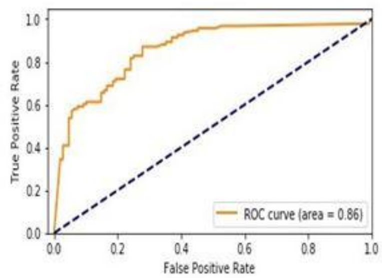
4 RESULTS AND DISCUSSION

The PPG optical mechanism enables clinicians to expand the scope of the screening devices and their applicability. New advancements in medicine have made it possible to incorporate PPG into wearable devices for real-time monitoring and prediction of cardiovascular disease. The quality of PPG measurements is also an advantage, as the device measures several variables to quantify cardiac activity and normal blood volume. The PPG typically uses a series of pulse and peak detections to measure oxygen saturation and heart rate. Cardiovascular disease with a focus on arterial disease is one of the few targets for photoplethysmography. The research was conducted on super-intending ML and deep learning classification methods by combining RF, CNN, and LSTM. This research aims to forecast whether the subject will develop cardiovascular disease or not.

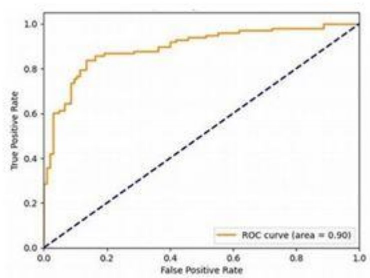
4.1 The Evaluation Process Used

There are five components in the evaluation process: the confusion matrix, precision rate, precision, recall, sensitivity, and F1 score. The confusion matrix is a table. With both true and predicted values, these can be canalized into the true positive and the true negative. The evaluation process is composed of four models: the first one is a True Positive (TP), where the values are recognized as true. The second model is False Positive (FP), which is identified as being true despite being false. In the third case, the value is true, but a False Negative (FN). The fourth model is defined as the True Negative (TN). Then the value is negative and is recognized as such.

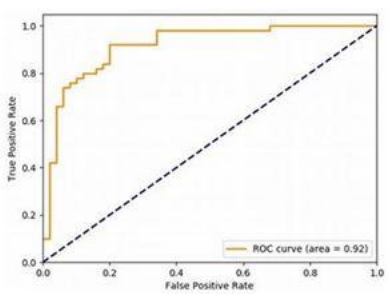
Figure 6. ROC curve and Confusion matrix of RF, CNN, LSTM



640	**107**
10	**11**



604	**123**
0	**5**



579	**72**
102	**15**

4.2 ROC Curve

Receiving Operating Characteristics (ROC) curves are used in machine learning to assess models, in particular when data is skewed, by visualizing their performance. The ROC curve is a graph that represents how well a classification algorithm performs at all classification thresholds. A ROC curve plots the following two variables:

i. Rate of true positives
ii. Rate of false positives

The True Positive Rate (TPR), is known as the probability of the observations that are predicted to be positive and are positive, given in eqn.2.

$$TPR = \frac{TP}{TP + FN} \tag{2}$$

In contrast, the False-Positive Rate (FPR) is the probability of the perception that its prognosis is positive but ends up being negative. The False Positive Rate (FPR) is described as in eqn.3.

$$FPR = \frac{FP}{FP + TN} \tag{3}$$

Consider heart data, which has 13 features: age, gender, smoking status, blood glucose level, height, weight, blood pressure, and cholesterol. The goal is to determine whether a particular individual has cardiovascular disease based on the above features. An example of this kind of problem is a binary classification problem. Alternatively, it could be dividing the population into two categories. For example, suppose there are 100 samples (each sample corresponds to one patient's information) out of which 90 samples are positive (they have heart disease). Therefore, the classification is correct because all 100 samples (100 patients) have heart disease. The accuracy of 90% was achieved without ever building the model. The dataset appears to be skewed, which means there are a greater number of positive samples (patients with cardiovascular disease) than negative samples (patients who do not have cardiovascular disease). Therefore, it is not advisable to decide on the best model by focusing solely on accuracy. This does not represent the data completely. Sometimes may get high accuracy, but the model will probably not perform so well on real-world samples. Therefore, ROC becomes more important as an evaluation metric.

Visual interpretation of data is easier with a simple graphical approach by using this ROC curve. It computes accuracy as a composite measure of the whole range of the test without taking prevalence into account, simplifying sampling. The threshold can be determined using any cut-off value. It is possible to calculate useful summary measures (e.g., the area under the curve). It is possible to compare two or more curves (e.g., comparing a new test with a previous one). Instead of predicting classes directly, it can be more flexible to predict the probability of an observation belonging to each class. A key reason for the flexibility is that probabilities can be interpreted differently based on different thresholds, which allows the operator of the model to balance concerns regarding the representation of false positive and false negative constructed by the model. Logistic regression is an analytical technique that is recognized by the approximate regression model when the response variable is binary. To estimate how well the logistic regression model, inserted into the database, can look at two metrics as given in eqn.4 and Eqn. 5.

Precision is followed by specificity, which is a ratio. True Negative cases group as negative: therefore, it measures how adequately the classifier recognizes negative cases, also called a True Negative.

$$\text{Accuracy} = \frac{TP + FN}{TP + FP + TN + FN} \tag{4}$$

Specificity: The chances that a model will predict a negative result for observation if the result is negative. To check the performance of the model, accuracy is applied. This variable is defined as the sum of True Positives and True Negatives divided by the sum of True Positives, True Negatives, False Positives, and False Negatives as given by Eqn 5.

$$\text{Specificity} = \frac{TN}{TN + FP} \times 100 \tag{5}$$

Sensitivity: The probability that the model will predict a positive result for observation if the result is positive as given in Eqn. 6.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \times 100 \tag{6}$$

There is sensitivity to what proportions are in reality. A positive case was predicted to be positive (or TP). The term "sensitivity" refers to recall as well. Further, a healthy person was predicted to have a harmful diet. A comparison of the results obtained by various researchers in terms of their CVD predictive performance is shown in table 3.

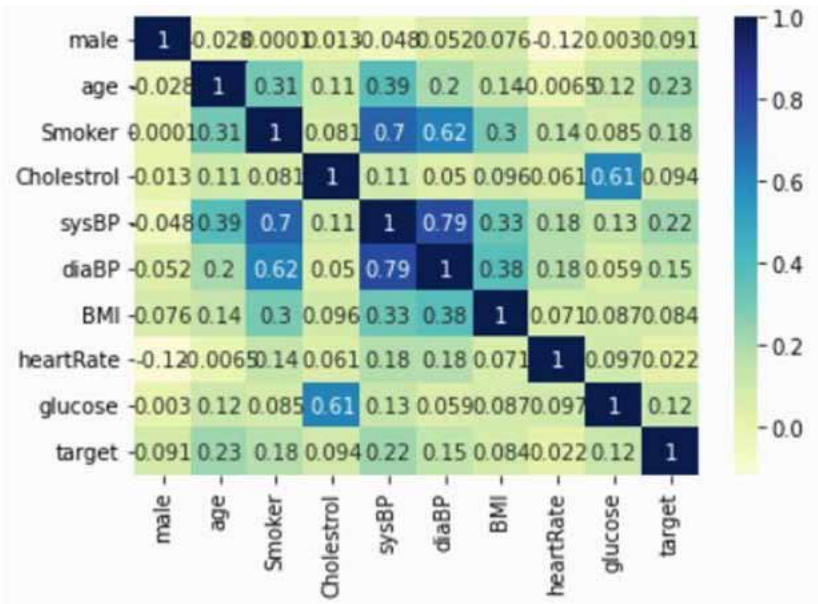
Table 3. Performance metrics of CVD prediction by various approaches

Author	Techniques	Accuracy
Wajid Shah et al.	Naive Bayes Decision Tree K-Nearest Neighbor	90.59% 82.31% 45.67%
Baban Uttamrao Rindhe et al.,	Support Vector Machine Random Forest	84.0% 80.0%
Ibrahim Abdel Motaleb et al.,	Radial Basis Function Back Propagation Network	98.0% 90.8%
Devansh Shah et al.,	Naive Bayes CNN Decision Tree RF	88.15% 90.78% 80.26% 86.84%
Kumar Dwivedi	Naive Bayes Classification Tree Logistic Regression Artificial Neural Network SVM	83.0% 77.0% 85.0% 84.0% 82.0%
The proposed model	LSTM CNN Random Forest	98.82% 95.78% 84.76%

4.3 Correlation Heat Map

A correlation plot is a plot of the covariance matrix or another metric that determines the strength of a linear federation. This matrix represents the magnitude and direction of the continuous relationship between the two parameters, with permit values ranging from -1 to 1. The covariance matrix functions provide information about the correlations between coefficients. This can be used to examine whether particular random variables have a relationship with one another. This is a great way to visualize correlation matrices as heat maps to pick out the correlations between features. The relationship between gender, age, smoking status, cholesterol, hypotension, hypertension, body mass index, pulse rate, and blood dextrose levels are expressed as a graph as shown in figure 7.

Figure 7. Correlation heat map



The linear relationship of a continuous variable is defined using dataset correlation. A correlation matrix is a square with equal variables in its rows and columns. The line at 1.00, running from top left to bottom right, is the main diagonal, showing that each variable is always perfectly correlated with itself. This matrix is symmetrical, mirroring the matrix below the main diagonal in the same proportions shown above in the heat map. There are three main types of input data for building heat maps: wide format, correlation matrix, and long format. The following steps show how to generate a correlation heat-map:

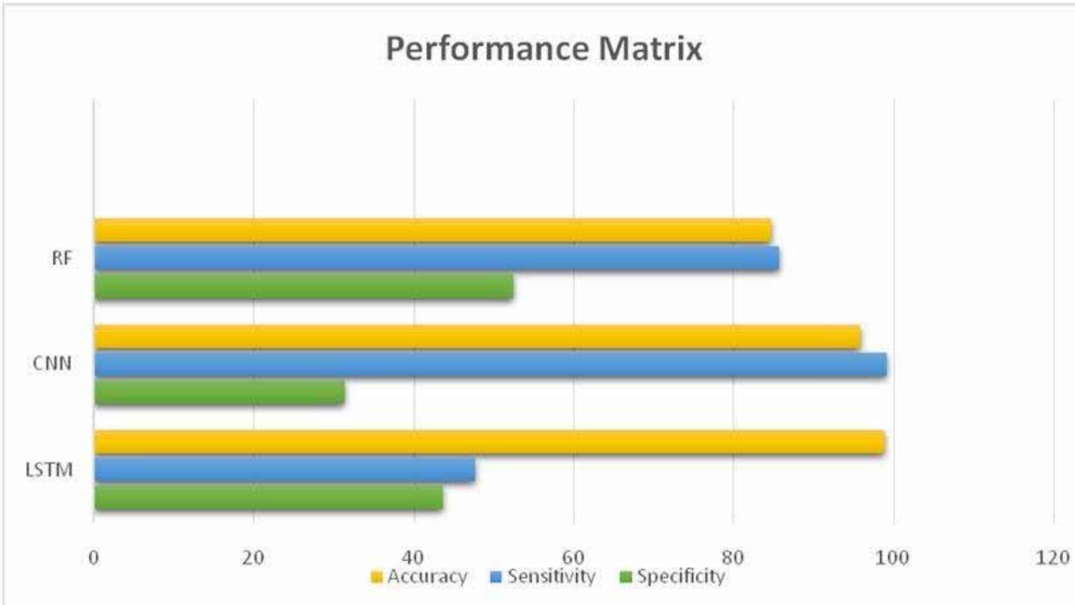
- First import all the modules.
- Second, import a file that stores the data.
- The third plot of the heat map.
- Fourth plot with matplotlib.

The heat map contains values representing different shades of the same color for each displayed value. In general, darker shades of a chart represent higher values than lighter shades. Before determining the correlation, we need to calculate the covariance of the two variables under consideration. The correlation coefficient is resolved by using the formula.

$$\text{Correlation} = \rho = \frac{Cov(X,Y)}{\sigma_X \sigma_Y} \tag{7}$$

Correlation between two random variables or two-dimensional data does not necessarily imply causation.

Figure 8. Performance metrics of proposed work



5 CONCLUSION

We can construct intelligent technology that can anticipate disease using susceptibility, reducing money and time for health checkups and tests. It is possible for patients to independently monitor their health and take precautions and remedies in the early stages of the disease. Various ML and DL approaches can be used by apps to accurately acquire and respond to user behaviors based on previous confessions. The development of a tool for predicting CVD successfully and splendidly requires an increasing number of deaths. However, the application's success depends on the precision of the classification program. The purpose of combining multiple algorithms is to improve performance. Unable to identify CVD at that very early stage will have a very slim probability of being cured. Hence, the proposed technique can produce the best possible predictions with high accuracy. The ultimate goal of our research is to enable proper and straightforward communication between medical professionals and patients without the need to visit a medication center and to make a healthcare app to prevent CVD to avoid future discomfort. Users can transmit the examined outcomes as images and upload them into real-time systems using DL. It can also use this method to predict lung diseases in the future.

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