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INTERNET OF THINGS AND MACHINE LEARNING IN AGRICULTURE

TECHNOLOGICAL IMPACTS AND CHALLENGES

Edited by Vishal Jain, Jyotir Moy Chatterjee, Abhishek Kumar and Pramod Singh Rathore

FRONTIERS IN COMPUTATIONAL INTELLIGENCE

Vishal Jain, Jyotir Moy Chatterjee, Abhishek Kumar, Pramod Singh Rathore (Eds.)
Internet of Things and Machine Learning in Agriculture

De Gruyter Frontiers in Computational Intelligence

Edited by
Siddhartha Bhattacharyya

Volume 8

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ISBN 978-3-11-069122-1
e-ISBN (PDF) 978-3-11-069127-6
e-ISBN (EPUB) 978-3-11-069128-3
ISSN 2512-8868

Library of Congress Control Number: 2020948394

Bibliographic information published by the Deutsche Nationalbibliothek
The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available on the Internet at http://dnb.dnb.de.

Cover image: shulz/E+/getty images
Typesetting: Integra Software Services Pvt. Ltd.
Printing and binding: CPI books GmbH, Leck

www.degruyter.com

To our parents and well-wishers

Preface

Agriculture is one of the most fundamental human occupation. As long as we have pursued it, we have tried to master it. Better techniques produce greater yields. This, in turn, kept humans happier and healthier – and helped birth modern society as we know it. However, there is only one hitch in this success story. As our farming capacity has expanded, usage of resources such as land, fertilizer, and water has grown exponentially. Environmental pressures from modern farming techniques have stressed our natural landscapes. Still, by some estimates, worldwide food production will need to increase by 70% by 2050 to keep up with global demand. With an increase in global population, it falls to technology to make farming processes more efficient and keep up with the growing demand. Fortunately, the combination of more data from the Internet of agricultural things and new machine learning capabilities can contribute a crucial part.

Machine learning and the Internet of things (IoT) play a very promising role in the agricultural industry; some of the examples are an artificial intelligence-programmed drone to monitor the field, IoT-designed automated crop watering system, and sensors embedded in the field to monitor temperature and humidity. Agriculture industry is the largest in the world, but when it comes to innovation, there is a lot more to explore. IoT devices can be used to analyze the status of crops. For instance, with soil sensors, farmers can detect any irregular conditions such as high acidity and efficiently tackle these issues to improve their yield. The data gathered from sensors allows us to apply analytics and get the insight that can aid decisions around harvesting.

In this book, we try to explore the impacts of machine learning and IoT in the agriculture sector and to point out the challenges faced by the agroindustry which can be solved by both machine learning and IoT.

Chapter 1 initially introduces the IoT architecture and the various protocols used to perform the data exchange between connected devices, and later discusses what machine learning is and their various categories.

Chapter 2 focuses on a long-term strategy by incorporating research and innovation for a sustainable agricultural system based on technologies such as the IoT and machine learning that play a significant role to advance sustainable farming and food nutrition.

Chapter 3 provides a detailed description of machine learning and its relationship with IoT, and also different applications of IoT where machine learning helped to make the intelligent system and the futuristic scope of IoT and machine learning and how these two technologies help in different areas such as smart city, smart human, and smart farming.

Chapter 4 highlights recent state-of-the-art work done with IoT and machine learning in the agriculture field and the challenges of respective technologies in this sector.

https://doi.org/10.1515/9783110691276-202

Chapter 5 highlights an overview of the modern technologies deployed to agriculture and proposes an abstract of the present and possible applications, and elaborates on the challenges and suitable explanations and execution.

Chapter 6 discusses Kaa, an IoT-based platform for smart farming that makes farmers reply instantly toward developing issues and modifications in encompassing conditions as well as examine their benefits.

Chapter 7 focuses on the benefits and technologies required for implementing smart farming.

Chapter 8 discusses various tools and techniques for smart farming using IoT that will significantly increase the farming outcome.

Chapter 9 aims at giving a detailed understanding of the IoT-based smart farming ecosystem and each of its elements with real-world use cases and illustrations.

Chapter 10 presents a novel smart farming enabled IoT-based agriculture toolkit Kisan-e-Mitra for soil quality analysis, testing, and recommendation.

Chapter 11 presents a discursive literature survey on the applications of artificial intelligence techniques in plant disease detection.

In Chapter 12, the convolutional neural network (CNN) model is used on 2,000 images to identify the wheat rust disease in an unseen leaf image.

Chapter 13 tries to introduce briefly the relevant concepts of plant disease detection and to explore how image-based plant disease detection technology can provide early detection of plant diseases.

Chapter 14 presents a review of the research works in rainfall forecasting using machine learning techniques with special emphasis on India.

Chapter 15 focuses on early disease recognition which requires higher resolution images.

Chapter 16 aims to exhibit deep learning capabilities to detect plant disease using images.

Chapter 17 explains how deep learning can be used for plant disease detection.

Chapter 18 includes an explanation about CNNs, their fundamental building blocks, and the details of different modern CNN architectures such as LeNet-5 and AlexNet.

We thank all the authors for their valuable contribution which makes this book possible. Among those who have influenced this project are our family and friends, who have sacrificed a lot of their time and attention to ensure that we remained motivated throughout the time devoted to the completion of this crucial book.

Acknowledgments

I would like to acknowledge the most important people in my life, that is, my grandfather late Shri. Gopal Chatterjee, grandmother late Smt. Subhankori Chatterjee, father Shri. Aloke Moy Chatterjee, mother late Ms. Nomita Chatterjee, and uncle Shri. Moni Moy Chatterjee. This book has been my long-cherished dream which would not have been turned into reality without the support and love of these amazing people. They have continuously encouraged me despite my failure to give them proper time and attention. I am also grateful to my friends, who have encouraged and blessed this work with their unconditional love and patience.

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https://doi.org/10.1515/9783110691276-203

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https://doi.org/10.1515/9783110691276-205

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Part I: **Machine learning and Internet of things in agriculture**

Parul Verma and Umesh Kumar

1 Smart farming: using IoT and machine learning techniques

Abstract: Internet of things (IoT) and machine learning (ML) together have a great impact on each domain. The agriculture domain is not an exception to it as it helps in the transformation of old-fashioned farming practice to smart farming. As we all know, the global population is increasing very fast and will be about 9.8 billion by 2050, and there is a drastic fluctuation in the weather around the world due to global warming. In order to feed this massive population in this harsh environmental condition, food productivity must be increased. So, there is a need to adopt smart farming in the agricultural industry.

In this chapter, initially, we introduce the IoT architecture and the various protocols used to perform the data exchange between connected devices. Then we discuss about what ML is and its various categories. At the end of the chapter, we address the various challenges farmers face with the traditional method of farming and how smart farming powered by IoT and ML will improve the agriculture operations from the sowing of seeds to till harvesting of the crop.

Keywords: Internet of things, machine learning, smart farming, applications, challenges

1.1 Internet of things

In the last few years with the successive expansion of information technology, the scope of the Internet has expanded to not only connect the two or more computers but something more than that. Now, the Internet is not limited between two computers, and connects different things that are around us like bulb, air conditioner, refrigerator, washing machine, watches, car, and so on. Interconnection of these things with the Internet introduces the term called the Internet of things (IoT) which is an emerging technology these days. In recent years, there is an exponential growth of IoT devices, which plays an important role in our daily lives. IoT keeps on transforming industries to work smarter either in the field of agriculture, healthcare, and manufacturing, and everything in between. By seeing the impact of IoT devices in

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https://doi.org/10.1515/9783110691276-001

various fields, it is predicted that around 50 billion IoT devices will be connected to the Internet by 2025.

IoT is a giant network of interconnected devices. These devices are able to interact with each other over the Internet and have the capability of sending data, receiving data, and making a decision without human intervention.

Let us take an example of a smart home to understand IoT application. A smart home consists of many objects that are interconnected. It includes smoke detectors, home appliances, bulbs, windows, AC, doorbell, and so on. Suppose that while leaving the office a person forgets to switch off the bulb; in this case, he/she will switch off the light with the help of his/her smartphone which is configured with it. He/she will get a notification when someone presses the doorbell and can remotely switch on AC to make the room cool before reaching home. Fig 1.1 provides the basic application areas of IoT.

Figure 1.1: Internet of things.

1.1.1 IoT architecture

In general, there are three major layers in an IoT architecture but these layers are getting more advanced as new technologies are introduced to improve the performance of IoT devices. Sethi and Sarangi [1] have stated architecture, protocols, and applications of IoT. Fig 1.2 provides the IoT Architecture.

IoT devices: Sensors connected to IoT devices are able to collect live data from the surrounding environment. Basically, it is a source data, and different types of sensors will perform their task accordingly; for example, temperature sensor will sense

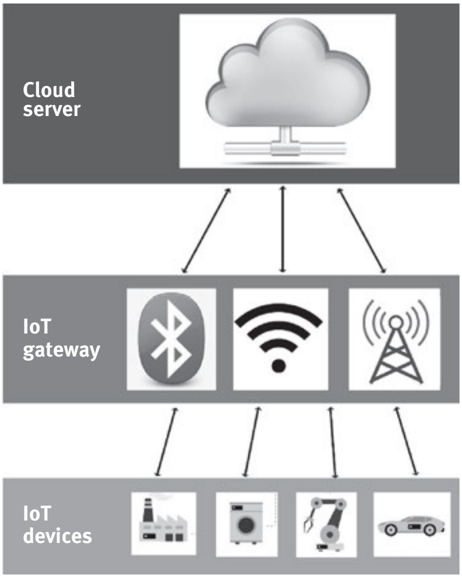

Figure 1.2: IoT architecture.

the temperature and motion sensor will sense the motion. IoT devices collect the information gathered by sensors and pass them to the IoT gateway.

IoT gateway: IoT data acquisition systems and gateway that collects the large volume of raw data will translate into meaningful data streams by performing initial processing and transfer it to the cloud server for further processing and analysis. Data will transfer through Wi-Fi, Bluetooth, WAN, ZigBee, and so on.

Cloud server: It is a centralized server where data are received, stored, processed, and analyzed in depth to perform the specific task. This is the place where machine learning (ML) is introduced, and various algorithms are working to analyze the data to take a decision. Once the data are processed and analyzed, the result is sent to the end-user either by alarms on their phones or sending them notification through email or text message to act on it. For example, if someone presses your doorbell, you will get a notification on your phone.

1.1.2 IoT protocols and standards

IoT protocols are a set of rules that allow the exchange of data between various connected devices in a structured and meaningful way. As mentioned in the previous section, data collected from various sensors are transferred to IoT devices, then forwarded to the gateway and then reached to the cloud server for processing, and finally, the resultant is transported to user applications. Shadi et al. [2] explained the various protocols involved in data communication from one layer to another layer. The IoT system can function and transfer information with the support of IoT protocols and standards.

IoT protocols can be classified into two major types: IoT network protocols and IoT data protocols.

1.1.2.1 IoT network protocols

It is a protocol that is used to connect devices over the network. These protocols permit end-to-end data transmission within the specified network boundaries. The following are the various IoT network protocols.

Bluetooth: This wireless technology is quite popular and used for short-range communications. It operates at 2.4 GHz in industrial, scientific and medical radio band (ISM) band. It operates in two modes as a master and as a slave. A master initiates an exchange of data and the slave responds to the master. Each Bluetooth device may be a master or slave at any time, but not simultaneously. Bluetooth low energy is a newly introduced protocol under IoT protocols, which is used to achieve the functionality of Bluetooth over low power consumption.

ZigBee: It is an IoT protocol that supports a low rate of data transfer between short distances. The range of connectivity is 100 m between two nodes. It also operates at 2.4 GHz and is most commonly used in home automation. It is easy to install and maintain.

LoRaWAN: It stands for long-range wide-area network. It is an IoT protocol for a wide area of the network which covers long range and is supported by devices that consume less power. This protocol is mainly used in smart cities where millions of low-power devices are installed. The LoRaWAN uses varied frequencies in a variety of networks. In the urban area, the range is 2–5 km, and in a suburban area about 15 km.

Wi-Fi: It is also one of the most commonly used techniques for communication when we need a large quantity of data to be transferred at high speed. The frequencies are 2.4 and 5 GHz bands. It covers approximately 50 m but consumes more power. It is working with the Internet protocol standard.

1.1.2.2 IoT data protocols

These sets of protocols provide end-to-end communication at the other side, which is the user's side through hardware devices, and do not require any Internet connection. IoT data protocols use the wired or cellular network for connectivity. The following are the popular IoT data protocols.

Message queue telemetry transport (MQTT): It is a message protocol and preferred for all IoT-based devices. The basic utility of MQTT is to collect data from heterogeneous devices. It also facilitates remote monitoring of these devices. It works on the TCP for reliable transmission. MQTT protocol consists of three components: subscriber, publisher, and broker. The publisher generates and transmits data to the subscriber and takes the help of a broker in this process. The basic role of a publisher is to check the authenticity of the publisher and subscriber.

Constrained application protocol: It was designed to translate the hypertext transfer protocol model so that it could be used in limited gadgets. This protocol works on the request–response model between client and server. It establishes secure communication using user datagram protocol between two connecting points.

Advanced message queuing protocol (AMQP): The basic role of this protocol is to transmit data to and fro between the cloud and other connected devices. The data transmission is secure and seamless. It is an application-layer protocol and designed for the middleware environment. It consists of three necessary components: exchange, message queue, and binding. The role of the exchange is to receive a message and put them in a queue. The messages received are being stored by message queue until these messages are being utilized by the client app. The role of the binding component is to bind or connect the exchange and message queue component.

Lightweight machine to machine: This protocol is being used for the self-monitoring of machines. As per the changes in the environment, the system makes required changes to be adapted in the changed environmental conditions. Its basic role is to manage lightweight devices that use low power.

Extensible messaging and presence protocol (XMPP): This protocol is based on extensible markup language (XML) language and is used as a communications protocol. For exchanging messages in factual time, this protocol makes use of a push mechanism. The protocol allows the various modes of communication like multiparty chat, voice and video calls, collaboration, lightweight middleware, content syndication, and generalized routing of XML data. However, there are certain limitations of this protocol as it does not offer quality of service and end-to-end encryption.

1.2 Machine learning

ML is the hottest trend in today's market, and it is predicted that by 2025 nearly 50% of the products will be based on ML. ML is a subclass of artificial intelligence, and it is a technique where machines learn automatically from past experiences and not being programmed for it explicitly. It uses statistical methods to enable the machine to improve the experience. It is a core of many technologies advancement like a self-driving car by Tesla and face reorganization in Apple iPhone.

In traditional programming, the user will write a program to perform a specific task. Suppose that there is a program to perform the addition of two numbers, in this case, the user will give two inputs like x1 and x2 and the user will get output y = x1 + x2. The equation is presented in Fig 1.3.

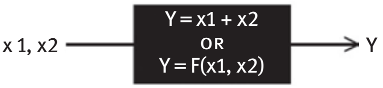

Figure 1.3: Traditional programming.

But in ML, the machine will learn by itself with the available input and output data and will generate an ML model. That model in the future will be able to predict the output for any input data. Suppose that there is a training input data X and training output data Y as given in Table 1.1.

Table 1.1: Training input/output data.

Training input data X	Training output data Y
2	6
3	9
4	12
5	15
6	18
7	21
8	24

This data helps the machine to learn that output(Y) is three times input(X) data and generates an ML model. **Y = 3 multiply by X** The fig 1.4 presents the equation.

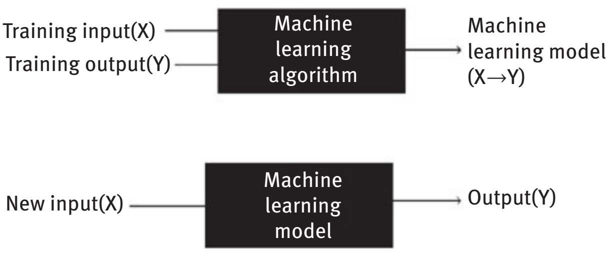

Figure 1.4: Machine learning.

ML algorithms tend to make a mathematical model which is based on sample data technically known as “training data.” The model is used further to make decisions and predictions based on that training data and is not being programmed explicitly to do such tasks. Sun et al. [3] surveyed various techniques of machine learning and its application in wireless networks.

1.2.1 Classification of machine learning

Supervised ML: In supervised ML, the machine is trained using labeled training data. Here, trainer is having input data as well as output data known as training data. The machine is trained with training data under the supervision of trainers. Learning will stop when the machine achieves an acceptable level of performance. Finally, the machine is ready to predict the output for any new set of input data.

For example, suppose that in an organization, biometric machine is trained by giving the thumb impressions of an employee from a different angle. Once the machine is trained, it will label that impression with the employee name or employee ID, and in the future, employee will be easily identified with his thumb impression.

Unsupervised ML: In this type of ML, machine is trained by unlabeled data. In unsupervised learning, we have only input data, and no output data are available. Training data are grouped in a different cluster based on their characteristics and each cluster is labeled.

For example, suppose that we have data of some cricketers like name, total run scored, and several wickets taken. The trainer will train the machine in such a way that if any cricketer scored more runs but took fewer wickets, then that cricketer will be labeled as a batsman, and if scored less runs and took more wickets, then that cricketer will be labeled as a bowler. So, in the future, machine will easily predict whether the cricketer is a batsman or a bowler.

Reinforcement ML: It is also called as semisupervised ML. In this type of ML, a large amount of input data are available but only some of the data are labeled. This method is lying between supervised and unsupervised learning. It is based on reward-based learning or work on the principle of feedback.

For example, suppose that the trainer will give a dog image as input to the machine to check whether the machine identifies it or not. If the machine identifies it as a cat image, then the trainer will give negative feedback to the machine by saying that it is a dog image. So, next time when there is the input of the dog image machine will identify easily.

1.3 Smart farming

At the beginning of the twentieth century, there were many innovative mechanical machines brought into focus to improve farming. Farming and agriculture industries are always relying on various innovative ideas and techniques to increase the productivity of crops with less investment and low risk. To achieve this motive, in the last few years, IoT and ML played an important role in agriculture industries. Varghese and Sharma [4] explain the affordable smart farming using IoT and ML. It allows many smart devices to increase agriculture production at a lower cost. Application of IoT in agriculture helps to overcome various problems like extreme weather change and drying of land, which directly impact the yield of crops. Now there is hope due to the rapid development of IoT applications in the field of agriculture which transforms the traditional method of farming into smart farming.

Smart farming mostly denotes the usage of IoT solutions in agriculture. IoT application in agriculture includes automatic irrigation, remotely monitoring the crop, weather forecasting, optimal time to plant and harvest, early detection of infections or pests, determine fertilizer based on soil chemistry, smart logistics, and resource sharing. Smart farming is an effective way of doing agriculture which improves the quality and quantity of products at low risk.

1.3.1 Challenges of traditional agriculture

- Irrigation problem due to rising climate change
- Crop failure due to the outbreak of insects/diseases/pests
- Monitoring of crop
- Logistics related to agriculture
- Selection of seeds
- Selling of crops
- Demand for more food

1.3.2 Benefits of smart farming

Smart farming basically exploits the potential of the latest technologies like big data, cloud, and IoT to draw the maximum output from agriculture which is somewhat hindered using traditional methods of farming. Following are the benefits that farmers can attain by using concept of smart farming-

- **Automatic irrigation:** To fulfill the concept of automatic irrigation, sensors are being used in the field which helps in collecting information of environmental factors like temperature, humidity, and soil moisture levels. This information helps in the prediction of the requirement of irrigation in fields.

Farmers can do the irrigation either automatically or manually. It helps in proper utilization of water and avoids wastage of water. The moment irrigation is required, farmers will get the alert message on their phone and inform when the task is over.

- **Weather forecasting:** It allows the farmers to make an effective decision like the optimal time for planting the crop and harvesting the ripped crop. It tells the farmers in advance about storm and unseasonal rain which can spoil the crop.
- **Early detection of infection:** With the help of drones, farmers can monitor the growth of the crop and detect early infection. It allows farmer to know the accurate time for spreading pesticides with the help of drones to control infection. Spreading of pesticides is done by drones in very little time and without manpower.
- **Remote monitoring of crops:** Installed cameras in the field keep on monitoring the crops and updating the farmers if any cattle enter the field.
- **Smart logistics and resource sharing:** Once the crop is ready, smart logistics will allow to easily track some tractors and some resources related to agriculture like wheat and rice cutter machine.
- **Selection of seeds:** There are various varieties of seeds available. By analyzing the production rate and quality of the product for the last 10–15 years, farmers can easily conclude which seeds improve the production.
- **Selling of crop:** If the farmer knows in advance exactly how much crop he/she is going to harvest, then he/she will prepare himself in advance to sell the crop in the market so that the product will not lie around unsold.

1.3.3 An example: automatic irrigation system configuration

In this section, we demonstrate automatic irrigation system, which allows the user to remotely control the water supply to the field once it becomes dry. Users can switch off or on the water pump manually through web application, mobile application, or automatically. Gutierrez et al. [5] developed an automated irrigation system to optimize water usage for agricultural crops. Fig 1.5 presents the block diagram.

Arduino Uno R3: It is an ATMEGA328p micro controller. The whole system is controlled through this microcontroller. It is programmed according to the requirement. It is used in many applications like security, home appliance, and many more. The device is able to connect the Internet as well. In this case, microcontroller and soil moisture sensor are used to record the moisture present in the soil. Based on the recorded data, irrigation system will work.

GSM module: The system used TTL SIM800 GSM module. It is very slim and compact. SIM800 delivers GSM/GPRS 850/900/1800/1900 MHz performance for voice, SMS, and data with low power consumption. LM317 is used to power SIM800 GSM module. In this case, it is used for sending the alert message to user on his mobile phone.

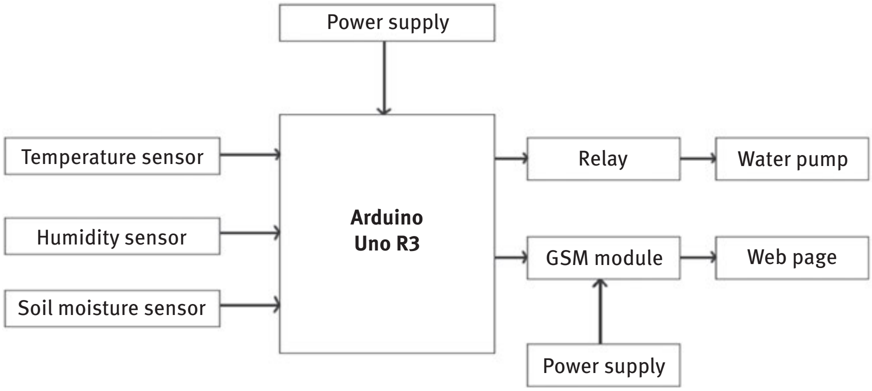

Figure 1.5: Block diagram of automatic irrigation system.

Relay: A 12 V relay is used to control the smart water pump. Single pole double throw switch has a single input terminal and two output terminals.

Soil moisture sensor: It is a sensor that is used to detect the moisture of the soil. It has both analog and digital outputs. It is based on the concept of open- and short-circuit concepts. When the soil is in dry condition, current will not flow through it and the circuit will act as open circuit, which results in high output, but when the soil is wet, the current will flow through the terminals and the circuit will act like a short circuit which results in low output.

Temperature sensor: LM35 is a temperature sensor that is used to measure the temperature of the environment.

Humidity sensor: It is used to measure the humidity in the environment.

Web page: It is designed for the user to interact with the system remotely. It allows the user to control the system remotely after getting the alert message. We can use Hypertext Preprocessor (PHP) to design the web page, and MySQL to record the data.

Power supply: It is used to supply the power to the whole system according to the requirement. It can be AC or DC power supply.

1.3.3.1 Working of system

This system can work in two modes: automatic mode or manual mode.

In the *automatic mode*, when the sensor placed to record the soil moisture identifies that moisture is less than the threshold value, which is being defined by the system, the water pump will get switched on automatically and will notify the end user. Once the moisture level reaches the threshold value, the water pump will be switched off automatically and the end user will be notified.

In the *manual mode*, when the sensor identifies that the moisture level is below the threshold, then GSM module will notify the end user, who will switch on the water pump remotely by using any web app or mobile application. Similarly, the user will switch off the water pump after receiving notification.

1.4 IoT and ML in agriculture

The IoT and ML are allowing agriculture to be done in a very effective way in terms of time, cost, production, and impact of the environment. In this section, we are going to review the various aspects while introducing IoT and ML in agriculture. The review mainly focuses on implementation and applications of IoT and ML in agriculture. And in the end, it reviews various challenges that IoT is facing and their solutions.

1.4.1 IoT and ML implementation in agriculture

In the last few years, IoT and ML play an important role in agriculture, which makes the farming to be done in a smarter way. Andres et al. [6] discussed the IoT implementation and its application in agriculture.

Here we are reviewing the IoT implementation in agriculture. There are basically three important layers in IoT architecture, which are physical layer, network layer, and application layer, but some authors divide it into more than three layers. Edge computing or fog computing layer is introduced between physical layer and network layer. This layer will improve the network performance by facilitating various benefits like quick response time, faster data transfer rate, and less congestion in a network. Srinidhi et al. [7] discuss numerous techniques to optimize network performance in IoT.

Physical layer: Physical layer includes physical objects (things) like sensors, actuators, and digital cameras. This layer is responsible for collecting the raw data with the help of various physical devices like sensors and actuators. Sensors are capable of sensing the environment around them and collect the information that is forwarded to IoT gateway. Actuators received the instruction from cloud to perform activation and deactivation of mechanical components. This layer also includes devices like transceiver, microcontroller, power supply, and converters – analog to digital converter (ADC) and digital to analog converter (DAC). Transceiver can transmit as well as receive the data. ADC and DAC will convert the data as per requirement, either analog data or digital data. Microcontroller controls the whole system and it is programmed according to the requirement. Pastor et al. [8] focus on precision agriculture using IoT architecture. Ferrandez et al. [9] discuss the architecture of IoT in the application of agriculture.

Network layer: Network layer is responsible for transferring the data to cloud using communication protocols. But in some architecture, initially, data will transfer to the intermediate platform and then finally transferred to cloud. Intermediate platform may include fog computing or edge computing. It will act as a gateway which collects the data and, in some cases, do the initial processing and then directs that information to user through Internet by using protocols such as MQTT, hypertext markup language or XMPP. Jawad et al. [10] described wireless sensor network in agriculture and classified and compared wireless sensor protocols. Alahmadi et al. [11] proposed various strategies that will provide the best connectivity like routing protocol, low power usage, and many more.

Application layer: The important services that the application layer performs are the access of data, its analysis, and storage. This layer will act as a user interface with the help of application programming interface. Data storage and data analysis are performed at cloud. Cloud computing makes the processing fast and allows independent execution of multiple applications. But the problem of latency and bandwidth, which is not acceptable in the IoT system, makes many researchers move toward the concept of fog computing and edge computing. Jayaraman et al. [12] presented the design of SmartFarmNet, which analyzes crop performance and provided recommendations accordingly. Gill et al. [13] proposed cloud-based automatic information system which provides required information related to agriculture automatically to the user.

1.4.2 Application of IoT and ML in agriculture

In this section, we review the various applications of IoT and ML in agriculture. These applications are categorized as monitoring, documentation, forecasting, and controlling. Kamilaris et al. [14] proposed the application of smart farming, like precision agriculture, which helps real-time data collection, processing, and analyzing that improves the productivity of crops.

Monitoring: Many sensors are deployed in the field to monitor the progress in agriculture. Bauer et al. [15] discussed the agriculture monitoring system in smart farming. Sensors are used to monitor the growth of the plant and any infection in leaf; to monitor the moisture in the soil and understand the soil chemistry; to monitor the temperature, humidity, and pressure in atmosphere; and many more. Storage of crops is also monitored to avoid the loss due to damage. Faraci et al. [16] proposed a network connectivity model to deploy the smart farming in rural areas where network connectivity is poor. Kodali et al. [17] proposed a design to monitor the soil moisture in a field and send an alert message when it is low either via SMS or email. Green et al. [18] discussed wireless sensors to collect the temperature and transmit to the gateway which helps to know the crop storage temperature and moisture levels.

Documentation: All collected data from various sensors must be documented that helps in analysis and decision making. These data will act as a sample data for further research. Kamilaris et al. [19] perform a review of the analysis of big data in order to understand the problems in agriculture. He also highlighted various opportunities of big data analysis in smart farming. Lyle et al. [20] discussed the yield mapping used in agriculture management and identified different types of yield mapping measurement errors.

Forecasting: Forecasting helps to know in advance about various things related to agriculture. It works basically on real-time data and historical data. Historical data help to design the various ML models that predict the correct time of irrigation, early detection of diseases in plant, fertilization, and when to harvest the crop. Balducci et al. [21] show how to implement ML on information collected from various sensors to enhance smart farming. Diedrichs et al. [22] discuss how ML algorithms are trained with past reading of temperature and help to predict the temperature in future.

Controlling: In any automated system, active monitoring plays an important role, which leads to control. For example, in case of automatic irrigation system, the water pump should be switched on once the soil moisture reaches its minimum level and automatically switched off once it reached the threshold value. Christensen et al. [23] describe weed control technologies, weed sensing systems, weed management models, and precision weed control implements. Midtiby et al. [24] proposed an algorithm which is being used to locate crop plants based on their seeding pattern.

1.4.3 Challenges of IoT in agriculture

Implementing IoT and ML in smart farming introduces various challenges that affect the performance of the systems. Interoperability is one of the major challenges and it arises due to different data formats, syntax, and encoding techniques. Elijah et al. [25] discuss various challenges and benefits of IoT and data analytics in agriculture. There are some other challenges as well, and these are categorized as device, network, and application.

General challenges are mainly concern about revenue and affordability, data heterogeneity, complexity, lack of products, scalability, flexibility, robustness, and fault tolerance.

Device challenges are basically concern about power consumption and harsh weather condition like temperature variation, heavy rainfall, humidity, and corrosion, which results in short circuit.

Network challenges include communication range, communication protocols, network management, network size, propagation losses, wireless link quality, latency, and throughput.

Application challenges include major security and privacy of data, quality of data, its accessibility, and further analysis of data.

1.4.4 Algorithms and models for smart farming

In this section, we discuss various algorithms that make the implementation of various technologies in agriculture successful. Basically, these algorithms are the core of these technologies. Smart farming makes the smart devices to do things smartly like automatic irrigation system, early detection of insects, weed detection, and correct time of harvesting. To achieve these things, systems work based on many intelligent algorithms. Some of these algorithms are discussed here to understand how these algorithms make the machine intelligent. These ML algorithms are categorized on the basis of regression, classification, clustering, and association. Efthimia et al. [26] discussed many algorithms that support the various activities in agriculture like yield estimation, plant health monitoring, vehicle guidance systems, and agricultural harvesting robots.

Artificial neural network (ANN): ANN is one of the important algorithms used in ML. It is a method of processing information very much like how brain processes the information. It consists of multiple processing elements (called neurons) to solve any specific problem. Neurons receive an input signal, compute it, and then produce the result. ANN is an excellent tool to teach machine when it is difficult to differentiate between patterns. Deep neural network is an advancement in ANN; it includes different layers of multiple layer networks. If we consider an example of ANN application in harvesting of fruits or crops, in this case, image processing technology is important. While harvesting with machine, it is challenging to identify the fruits and plants. So, various parameters like color, shape, or size values should be fed properly. Sabanci et al. [27] explained their method of wheat grains classification using ANN which is based on computer vision.

Convolutional neural network (CNN): CNN algorithm is mainly used to perform image recognition and image classification. CNN will take an image as input, process it, and then classify it. Weed detection is an example of CNN algorithm. Weeds affect the growth of plants and the quantity of final products. CNN will help differentiate between weeds from crops. So, machine will easily identify the weeds and destroy them. Kounalakis et al. [28] demonstrated the system based on robotics to control weeds. They utilized the framework that used the concept of image-based recognition.

Support vector machine (SVM): SVM is a machine algorithm which is used for classification as well as regression challenges. It can be applied to both linear and nonlinear problems. SVM uses kernel trick for the transformation of data, and based on this transformation, it observes optimal boundary between the various possible outputs. Insect detection in early stage is one of the examples. Pest control is also very important in farming. If it is not controlled at the correct time, it results in production loss and crop damage. Farmers are using pesticides to control the pest, but these pesticides produce dangerous consequences for public health, animal, and environment. So, the target is to reduce the usage of pesticides by early detection of pest. Ebrahimi et al. [29] utilized SVM classification for vision-based pest detection.

***k*-Means clustering:** *k*-means clustering is an algorithm that comes under unsupervised ML. In smart farming, it helps to predict and prevent the disease in plants by differentiating the images of leaf. Zhang et al. [30] proposed leaf image-based disease recognition using sparse representation. In this method, *k*-means clustering segments the diseased leaf image and then classifies diseased leaf images using sparse representation.

1.5 Conclusion

Smart farming is a hope to continuously improve the techniques of farming, which results in the quality and quantity of product at low cost and minimum risk. IoT-based applications allow the farmer to react more accurately on time. More accuracy means right time for irrigation, pesticides, harvesting, and many more. More accuracy also means proper utilization of resources like water, fertilizer, and logistics. All in all, we can say that smart farming is an effective system of doing agriculture in a sustainable way.

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2 Food security and farming through IoT and machine learning

Abstract: Agriculture plays a vital role in the Indian socioeconomy. In 1871, the Department of Agriculture and Commerce was started by Lord Mayo, the fourth viceroy of India, and A. O. Hume. On the basis of Famine Commission reports of 1880, 1898, and 1900, respectively, the government identified and set up a Department of Agriculture. In 1905, the Agriculture Research Institute became the Indian Agricultural Research Institute (IARI). From the IARI, the green revolution stemmed. After independence, the main challenge has been to generate enough healthy food with high nutrition for the Indian population. Article 47 states that public health with increased nutrition and standard of living is the first duty of the state, and thus the National Food Security Act 2013 has become a high priority of the government. Therefore, the varieties of high yielding crops were promoted in conjunction with excess use of chemical fertilizers, pesticides, and irrigation without knowing the negative impact on future farming and soil health. In recent years, some fruitful initiatives like the usage of innovative technologies and positive government policies have been taken in the agricultural sector to maximize the overall production rate with the required quality of soil and minimize the input cost. But, due to continuous growth in population, there is a huge need to produce nutrition-enriched crops to fulfill the hunger as well as maintain the soil health by promoting the use of biofertilizers and green manure, and controlled use of irrigation as per the necessity. In this chapter, our focus is to discuss a long-term strategy by incorporating research and innovation for a sustainable agricultural system based on technologies such as the Internet of things and machine learning that can play a significant role to advance sustainable farming and food nutrition. This may include methods to improve the soil fertility, to optimize the use of water (more crops per drop), to enhance farmers' well-being, to study the effect of weather changes on soil fertility, to strengthen social equity and local economy, and to promote the use of biofertilizers and green manure.

Keywords: sustainable farming, food Security, machine learning (ML), Internet of things (IoT), more crop per drop, green manure

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https://doi.org/10.1515/9783110691276-002

2.1 Introduction

Agriculture plays a vital role in Indian socioeconomy. In 1871, the Department of Agriculture and Commerce was started by Lord Mayo, the fourth viceroy of India, and A. O. Hume. Based on the Famine Commission reports of 1880, 1898, and 1900, respectively, the government identified and set up a Department of Agriculture. In 1905, Agriculture Research Institute became the Indian Agricultural Research Institute (IARI). From the IARI, the green revolution stemmed. After independence, the main challenge has been to generate enough healthy food with high nutrition for the Indian population. Article 47 states that public health with increased nutrition and standard of living is the first duty of the state, and thus the National Food Security Act 2013 has become a high priority of the government. Therefore, the varieties of high yielding crops were promoted in conjunction with excess use of chemical fertilizers, pesticides, and irrigation without knowing the negative impact on future farming and soil health. In recent years, some fruitful initiatives like the usage of innovative technologies and positive government policies have been taken in the agricultural sector to maximize the overall production rate with the required quality of soil and minimize the input costs. But, due to continuous growth in population, there is a huge need to produce nutrition-enriched crops to fulfill the hunger as well as to maintain the soil health by promoting the use of biofertilizers and green manure, and controlled use of irrigation as per the necessity.

From ancient times, agriculture has been playing a vital role in providing food for the sustainable growth of living organisms like humans and animals. It has also been found as a major source of income, especially in rural India. As we know, the major portion of the Indian economy is based on agriculture, and thus our economy moves around agricultural productivity. After independence, the government of India has launched various schemes such as the Integrated Production Programme in the 1950s and the Grow More Food Campaign in the 1940s to promote agriculture. The government has also taken some other initiatives like providing help to the farmers for their agriculture-related queries through online support and messaging services. Such initiatives help farmers to increase crop productivity thereby providing food to the society at large. Thus, the main aim of the government is to produce highly nutritious food for the growing population of the country at a low cost. In 2013, India became entitled to the tag of the seventh largest exporter of agricultural products in the world by exporting products worth $38 billion [1]. In the same year, India also became the sixth largest net exporter of agricultural products in the world [1]. Therefore, the varieties of high yielding crops were raised in conjunction with excessive use of pesticides, dye, chemical fertilizers, and improper irrigation without knowing its side effects on future farming and soil health. To resolving this problem some fruitful initiatives and innovative technologies are introduced by the government in the agricultural sector to maximize the overall production rate with the required standard of soil and minimize the input cost.

Due to high growth rate of population in India, we are highly focused on increasing the production rate in farming, which forces us to use an excessive amount of chemical fertilizers and water without knowing the nature of the soil, amount and frequency of water/fertilizer requirement, and the effects of weather change on a particular crop which gradually degrades the soil fertility and also affects the production rate.

To address such types of problems, sustainable farming is required which will give real-time information about the status of nutritive elements, required amount of water, right quantity of manure to be used with essential soil improvers, and selection of crop with respect to the health of the soil. Consequently, the use of biofertilizers and green manure will be promoted.

The idea of sustainable farming has been introduced to meet the nutrition-enriched food and market needs, without compromising the quality of food as per the needs of current and future generations. Such type of farming minimizes the use of harmful pesticides and chemical fertilizers that can harm the health of the farmers and consumers. It promotes the use of green manure and natural fertilizers with the help of which it supports the local economy and healthy food production.

To promote sustainable farming, Internet of things (IoT) and machine learning (ML) have been providing an intelligent system to overcome the limitation of the traditional farming practices, which are getting impractical to maintain the balance between demand and supply. IoT and ML are emerging as a helping hand in crop production to ensure the quality of food in terms of nutrition. For this very purpose, technologies such as IoT and ML can play a significant role in advancing the farming practices based on sensors, actuators, radio frequency identification (RFID), Global Positioning System (GPS), and supervised/unsupervised learning techniques. The system is based on IoT and ML monitor and can provide real-time information about soil health, crop life cycle, soil and air moisture, measurement of crop growth through crop height, frequency and amount of watering required for irrigation, required amount of manure, and so on.

In this chapter, our focus is to discuss a long-term strategy by incorporating research and innovation for a sustainable agricultural system based on technologies such as IoT and ML that can play a significant role in advancing sustainable farming and food nutrition. This may include methods to improve soil fertility, to optimize the use of water (more crops per drop), to enhance farmers' well-being, to study the effect of weather changes on soil fertility, to strengthen the social equity and economy, and to promote the use of biofertilizers and green manure.

2.1.1 Present scenario

As we can see, various factors are involved in affecting farming, such as variation in temperature, rainfall levels, and excessive use of fertilizers and pesticides, which deteriorate the groundwater. Soil degradation is another major issue that affects agriculture yields. This mainly happens due to wrong farming practices such as waterlogging, contamination by pesticides, and salting which results in loss of soil fertility.

The need for water is a prime requirement for the systematic growth of the crop. At the same time, lack/excess of water may harm the crop and also affect the water level. Hence, an effective water management system is required due to the uncertainty of the weather, drying of rivers, and decreasing water level. To overcome the issues related to water availability to the crops, different types of IoT sensors, such as moisture and temperature sensors, are being used to supply the real-time quantity of water to the crops [2]. In this context, different techniques have been developed to control the water supply and quantity with the help of the gateway based on microcontroller. Here, the microcontroller is programmed with soil moisture and temperature threshold values. This system allows inspecting the irrigation scheduling either through a mobile app or through the web page.

In a recent study, some researchers have found that traditional agricultural practices affect farming. This occurs due to the excessive use of chemical fertilizers and the unavailability of the intelligent irrigation system. Hence, in result decreasing the fertility of the soil and as well as agriculture yield. However, to overcome these issues, various techniques have been developed for monitoring and controlling precision agriculture [3].

However, in spite of the presence of various issues, gradual technological advancements play a significant role in the overall agricultural production as well as support farmers and other rural households in overcoming liquidity constraints and better management of risks with positive impacts on farm-level investment in agriculture. In recent years, some research initiatives have been taken in the direction of farmer's well-being by providing technologies to increase agricultural yields.

2.1.2 Literature survey

Over many thousands of years, agriculture has played a significant role in providing food for human beings. It has included the appropriate farming techniques for the sustainability of different crops in the changing environmental conditions. It is already known that sustainable farming and food security are based on using the natural resources in an efficient way. It can only be possible by following the appropriate nutrient cycle, nitrogen fixation, soil regeneration, use of green manure, and so on in food production processes.

The current human population in the world stands at around 7.8 billion, and it is expected to reach around 11.2 billion by 2100. So, to ensure nutrition-enriched and healthier food for the increasing population while maintaining the vital ecosystem and sustainable wildlife is a big challenge. Many research works are going on worldwide to overcome the current and future challenges of sustainable farming and food security, and research initiatives for the same are as follows:

Bargoti et al. [4] used the R-CNN in the detection of fruits from orchard. For this, they trained the network on three color images (BGR) of varying sizes. They used

VGG16 with 13 convolutional networks with ZF network to train the model. The result of the experiment was promising for two fruits (i.e., mangoes and apples). In research, Ferentinos [5] applied the convolutional neural network to recognize the plant disease. They trained the model on healthy and diseased plant images and found 99.53% accuracy in detecting diseased plants. A deep-learning-based technique has been discussed and applied by Kamilaries et al. [6] in various agricultural fields to enhance the classification and accuracy in processing the raw agricultural data. They found that deep learning can be implemented for different activities such as fruit counting, plant recognition, and future crop yield to get a high-accuracy result.

Yong et al. [7] developed an embedded intelligence system for the agriculture sector. The system is applicable for smart crop management, smart irrigation, smart farming, and smart greenhouses. Also, they presented a technology roadmap to clear the doubts in agricultural activities such as smart farming and smart irrigation. To address the sustainable food system, the European commission has launched a research and innovation program, Horizon 2020. Under this program, they study about the ecological techniques which are more suitable and applicable for sustainable farming. Over the period of 2014–2020, the European commission has sanctioned €240 million for sustainable farming through promoting organic and mixed farming. Under this program, various issues will be explored such as nitrogen fixing crops, organic farming practices, diversification and rotation [8].

Australian National University, in its research, has focused on three research topics for sustainable farming, that is, healthy farms, healthy farmers, and healthy profits. The overall objective of the program is in improving crop production, keeping the good mental health of the farmers, and ensuring the financial benefits to support farmers. In another study, they are looking at the benefits of ecosystem services provided through sustainable farming practices. These benefits are erosion control, carbon storage and its effective utilization, and maintaining biodiversity through habitat provisioning [9]. In 2017, the Department of Agriculture, USA, funded state-wide demonstration farms to apply soil health practices and to study their impact on cropping systems. Under this scheme, a soil health management system has been adopted through the soil health demonstration farms [10].

A center for agricultural development in Israel has provided training for 132 countries around 270,000 people. This training has covered various courses on new technologies related to agricultural development [11, 12]. In Nigeria, over 3,000 demonstration farms have been showcased by a fertilizer company to teach the farmers about modern farming practices [13]. Over 1,242 community demonstration farms have been established by the Ministry of Food and Agriculture, Ghana, to demonstrate the advanced agricultural technologies for sustainable farming [14].

In Kenya, a training program has been conducted for women to teach them about conservation agriculture. This training includes a study about legumes or crops to protect bare land through seasonal soil cover. This training helps to gain profit and food security through improved crop productivity and increased yields [15, 16]. An expert system named "PRITHVI" was developed by Prakash et al. [17]. This system was based on fuzzy logic to advise the farmer to increase the production of the soybean crop. Shirvavale et al. [18] implemented a system based on wireless sensor networks for farm management under different environmental conditions. This system ensures the required need of crops and soil to gain the optimum result in farming.

Ravichandran et al. [19] developed a system based on the APK platform. This system is designed not only to suggest the crop to the farmer but also to advise the farmer about the required amount of fertilizer to be used for a particular crop as per selection by the farmer. An expert system was developed by Shahzadi et al. [20] to provide expert information about the field condition to the farmers. This system consists of humidity, temperature, leaf wetness, and soil sensors. A prediction system has been developed by Patil et al. [21] to guess a grape disease in advance. Before developing this system, it was found that any disease in the grape plant can be noticed only after the plant was infected. And as a result, the whole vineyard gets affected. To overcome this issue, the researchers employed sensors in the vineyard such as leaf wetness sensor, temperature sensor, and humidity sensor for predicting the disease. Kodali et al. [22] presented an IoT-based cloud platform named Losant. This platform provides real-time monitoring of the agricultural field and provides alert messages through e-mail/SMS if any anomaly is found.

2.2 Background-related work

2.2.1 Internet of things

Various smart devices involved in IoT are interconnected to each other with the help of the Internet to communicate and share the data without human intervention. IoT includes software, physical devices, communication protocols, data, and services [23]. IoT also includes smart agricultural devices such as air and soil moisture sensors, objects equipped with a ground positioning system (GPS), and in-built sensors in a car to provide real-time alert to the driver about an unused seatbelt, opened car window, and presence of any objects at the back and in front of the car. A wireless sensor network is used in IoT to collect data from various types of sensors. IoT devices use routers/network devices for connecting and exchanging data over the Internet [24]. The collected data are then transferred using some standard wireless protocols to the dedicated server or on the cloud for further processing. The stored raw data is then processed to give the required information, and this will be further used to monitor the whole system. There are various application areas where IoT is emerging as a helping hand to perform smartly. Such applications include smart irrigation, home automation, drug manufacturing, smart cities, and disaster management. The fundamental architecture of IoT is shown in Figure 2.1.

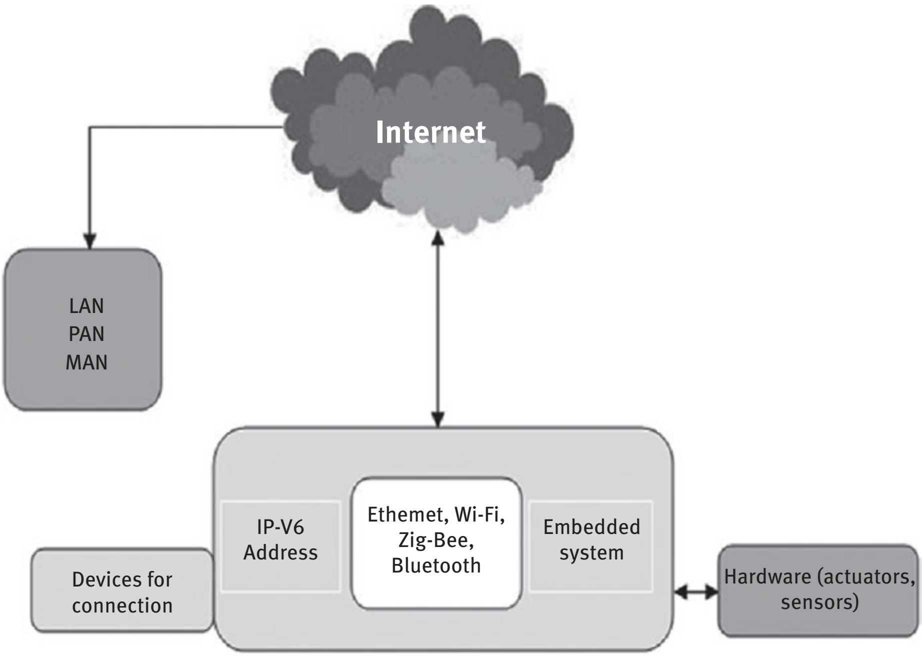

Figure 2.1: Fundamental architecture of IoT.

2.2.1.1 History of Internet of things

The word "Internet of things" was first introduced during the presentation at Carnegie Mellon University by Kevin Asthon in 1999 on Coca Cola vending machine. He was the cofounder and executive director of Auto-Id center, Massachusetts Institute of Technology (MIT). It was the first time ever an Internet-connected device had been used to tell whether the drinks loaded in the vending machine were cold or not. Kevin Ashton used RFID in his presentation to make it more effective in front of the senior management of P&G.

The term IoT can be defined as a particular time instant when the Internet is used to connect more than one object or thing to share data automatically rather than human intervention. According to the Cisco Systems, from 2008 to 2009, the term IoT was first originated. Between 2000 and 2010, the success of various projects and the presence of different practical applications became the main cause of the rapid growth of IoT in the society [25].

In 2010, the Chinese government included IoT in its strategic plan at the highest priority due to its wide applicability with the Internet. A company named Gartner first recognized the IoT as an emerging technology in 2011 to connect the devices smartly. In 2012, due to high publicity and applicability in various domains, IoT was used as a conference theme in one of the biggest conferences in Europe. Nowadays, IoT has been applied everywhere and has become an essential part of our daily life. We generally use IoT in home automation such as automatic control of room temperature and automatic management of home appliances.

2.2.1.2 Internet of thing (IoT) devices

IoT devices like smartphones, smartwatches, and other smart computing devices are interconnected to each other and share information smoothly over the Internet without any humans intervention. These devices are called smart devices due to their inbuilt high-definition technologies which help them to control and work remotely whenever it is required. A brief overview of some useful IoT devices is as follows:

2.2.1.2.1 Google home voice controller

This smart device can be used to control various activities through voice such as controlling and managing lights, media, television volume, and alarms. This device is also useful to manage the things remotely for the whole day remotely.

2.2.1.2.2 August doorbell cam

This is a very promising and applicable innovation of IoT. Through this device, you can manage the door-related activities like shutting and opening of doors from a remote location. It also allows tracking the motion changing activities at the doorstep.

2.2.1.2.3 Smart light switch

The smart light switch is used to manage the lights of your home through voice assistance software like Google Assistant, Alexa, Siri, or mobile device. We can set the schedule of our home lights to turn on and off at a specific time. Scheduling is very much helpful for the security point of view when you out of your home and it makes it look like you are at home. Also, this smart switch can be programmed to turn on all your lights together whenever some wrong activities are observed as when an intruder detected by the security system.

2.2.1.2.4 Thermostat easy temperature control

This device automatically controls the home temperature. It learns from the room environment and manages the room temperature accordingly.

2.2.1.3 Working of Internet of things (IoT)

IoT includes computing hardware devices such as sensors, actuators, processing units, and software that instructs what to do and how to do it. Here, sensors are used to collect data of various kinds (such as light, temperature, moisture, body movement, and heart beat), and devices like actuators are used to send and receive signals over wireless technology. In this context, the significant data is then used by the software to perform the task and satisfy the need of the user. Mostly, IoT devices are programmed and they work accordingly. But, it can also be programmed as per requirement. When we talk about the working of IoT, it means we talk about the prime components of IoT on which the IoT is based. These components are devices/sensors, connectivity, data processing, and user interface. Let us discuss these components as follows:

2.2.1.3.1 Devices/sensors

Devices/sensors are the main components of the IoT as shown in Figure 2.2. Sensors are used to collect data as per the problem statement. After that, the collected data is processed as per the need of the application. For example, on our mobile phones, we have built-in sensors such as cameras and GPS. Another example is the use of soil moisture sensor, which measures and collects the data about the water content in the soil. These sensors are specially programmed to collect a particular type of data to be used later.

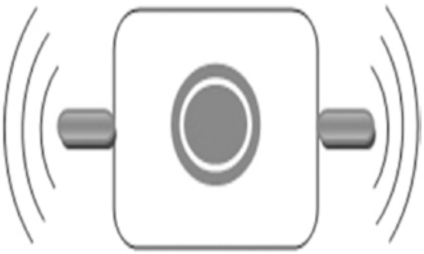

Figure 2.2: Device/sensor.

2.2.1.3.2 Connectivity

After collecting the data, it is sent to the IoT infrastructure which is also known as cloud server space. The connectivity between the devices is established with the help of a medium. This medium may be in the form of Wi-Fi, Bluetooth LAN, WAN, and cellular networks. The selection of the appropriate medium is very significant to ensure better outcomes. Mainly, the two factors such as the medium availability and speed of the medium are responsible for better connectivity. A symbol of connectivity is shown in Figure 2.3.

Figure 2.3: Connectivity.

2.2.1.3.3 Data processing

Once the data reaches the IoT infrastructure or cloud server through a connecting medium, processing of data takes place which helps to make the decision in the right direction and also suggests what action should be performed as per the requirement. Data processing and analysis may involve very simple tasks, such as checking the AC temperature, or complex tasks such as identification of intruder in the house, and the presence of the animal on the farm. Figure 2.4 represents the data processing component.

Figure 2.4: Data processing.

2.2.1.3.4 User interface

This is the last step that is used to inform the user about the action taken through the alert message or a notification message to the user interface. The user interface may be either a mobile application or a web application. The whole process starts with sensing the data by the sensor from the environment, and the analysis of collected data is performed over the IoT infrastructure. The outcome of the analysis is converted into the form of an alert message or notification and sent to the user interface if any wrong situation is analyzed. The user interface step is a very complex task, and the success of this step depends on the IoT platform and the technology that has been developed to perform the whole operation. A symbolic representation of the user interface is shown in Figure 2.5.

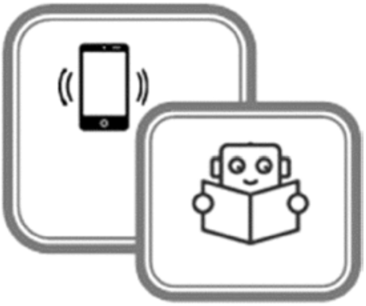

Figure 2.5: User interface.

2.2.2 Machine learning

In 1959, a new term "machine learning" was introduced by an American researcher Arutore Samuel in the field of computer science as well as artificial intelligence [26]. Nilsson's book came into the field of ML in 1960, usually on the principle of pattern classification, in 1981; a neural network was able to recognize 40 characters through a terminal in which the English alphabet, decimal number, and four special symbols were identified [27].

According to algorithms studied in the field of ML, Tom M. Mitchell says "A computer program is said to learn from experience 'E' with respect to the class of certain tasks 'T' and performance measurement P if its performance in tasks by 'T', as 'P' calculated, improves with experience 'E'." So one can say that ML is the study of computer algorithms that automatically makes continuous improvement through experience. It is a subset of artificial intelligence, algorithms that construct a mathematical model which is based on trained sample data, called as "training data," to perform without unambiguously programming forecasts or decisions. ML algorithms are used in a wide variety of applications, such as computer vision and email filtering, where it is difficult or effective to develop conventional algorithms to execute necessary tasks [28].

ML is closely related to computational statistics, which can predict the future through intelligence algorithms using computers, studying the mathematical optimization by improving techniques in the field of ML, distributing the domains of theory and application, data mining is a related field of study, which focuses on unaided as well as discovered data analysis, it can also be called predictive analysis of ML in business problems solution.

A good initiation of ML applications is trained from human knowledge exclusive of thorough programming. While showing the original information, these requests gain knowledge of raise, modify, and build up through themselves, in another way, with computers. ML discovers perceptive information without informing everywhere to appear. As a substitute, they do this by leveraging algorithms that study information in an iterative method.

2.2.2.1 Working of machine learning

The basic work of ML is to learn things and then use them in real life; for this purpose, the machine is first trained with data samples and after viewing its output the algorithm is improved, which increases the accuracy of the machine. ML algorithms need to be updated continuously and this update is gained through knowledge or experience working with unknown data. ML performs its function through a dynamic algorithm. To know whether the output of the ML algorithm is correct, for this purpose, the new input dataset is fed through an algorithm and then future output is verified through the output and if the output is not expected, then its deficiency is checked by changing the ML algorithm until the expected output is found.

2.2.2.2 Types of machine learning

ML has basically two types, which are shown in Figure 2.6.

2.2.2.2.1 Supervised learning

Supervised learning is used when the machine is to be learned by monitoring. It is basically a model that uses a labeled dataset to make predictions, where it gets to know the target answer when it reaches that level. In supervised learning, the goal is already defined in the machine as a program, and it has to reach its goal by finishing multiple tasks at once which takes this model training from its own experience and own accuracy [29, 30].

- Classification
  Classification is a process that divides data into classes: structured or unstructured data. The process starts with predicting the square of the given data points, and this process class is known as target labels and ranges.

- Regression
  Essentially regression is a statistical approach to find variables that associate association. In ML, it is employed to predict the outcome of an event based on the relationship between variables derived from the dataset. Linear regression is a type of regression used in ML.

2.2.2.2.2 Unsupervised learning

In the case of unsupervised learning, a particular pattern is detected by a dataset that refers to labels or known results, rather than unsupervised ML as ineffective ML methods are not directly applied to regression or single classification problems. This may be because the user is not aware of what the value of the output data might be, so it would be difficult to find different structures of the data, so in such a case, unsupervised learning is used [31].

– Clustering: Clustering permits automatically to divide datasets into groups based on similarity; however, cluster analysis shows the similarity between groups and does not treat data points as individuals. Therefore, cluster analysis similar to customer segmentation and targeting is a poor choice for applications.

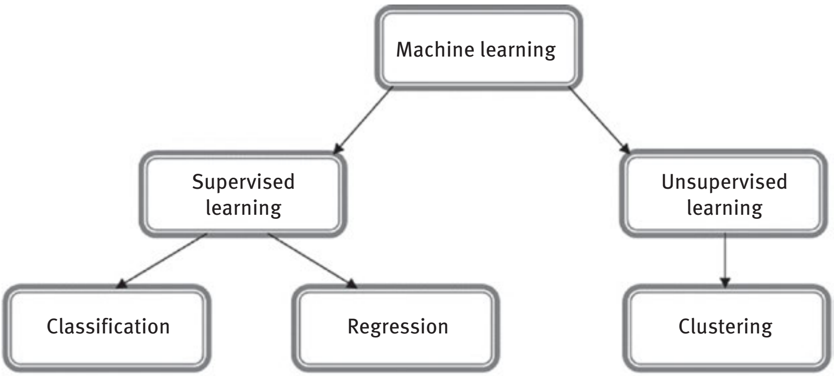

Figure 2.6: Types of machine learning.

2.2.3 Sustainable farming

Sustainable farming is an approach that helps to meet the food requirement and other societal needs without compromising the issues related to the quality required in the food for the current as well as the future generation. Such type of farming also promotes natural farming practices to sustain the quality of the soil and also maintain the required nutrition level in the food. In sustainable farming, we improve and maintain the fertility rate of the soil using natural practices like the use of green manure, minimal use of fertilizers, effective crop rotation policy, promoting organic farming, and maintaining the balance between the natural resources used and crop production. Such practice helps to preserve the ecosystem for a very long time and thus ensures the future of sustainable farming [32, 33]. The need for sustainable farming arises due to the unnecessary use of chemical fertilizers and pesticides without knowing the negative impact on soil and public health in the past. As a result, it becomes the cause of the reduction in soil fertility, lack of nutrition in the food, decrement in overall production as per demand, and hence affects the economy. The main objective of the sustainable farming is to apply smart farming system with the help of modern tools and techniques like IoT and ML to provide the real-time information about the required amount of water, natural manure, and rotation of crop as well as to promote natural fertilizers and green manure in the farming practices. The principles of sustainable farming are as follows:

- Generate an economical and effective food production system to get sustainable income.
- Develop rules for protecting territories and preserving biodiversity.
- Use natural resources in an optimal and efficient way to get the maximum output.
- Maintain a better quality of air, water, and soil. Improve and maintain the quality of water, air, and soil.
- Produce and distribute food efficiently.

2.3 Sustainable farming through Internet of things and machine learning

In recent years from the origin of the IoT, several smart devices and intelligent systems have been developed, which are interconnected to each another through internally connected medium and to store the data on a cloud server to process later as per requirement. The market of IoT is growing rapidly and companies are competing with each other for providing a better quality of service to the consumers [34, 35]. Also, ML techniques are very much applicable to IoT to process the huge amount of data received from the various IoT devices to predict the potential outcome for a given problem.

In the case of sustainable farming, the main objective is to attain enough amount of nutrition-enriched healthy food for society at large. Sustainable farming ensures the required production of crops keeping in mind for maintaining the required nutrition in the food, soil fertility, smart irrigation system, use of green manure, and proper management of the agrowaste materials to be used as natural manure in the crop field.

Nowadays, the intelligent system based on IoT and ML is rapidly changing traditional farming practices toward smart farming. The intelligent system can be used for analyzing the condition of the agricultural field based on the data sensed by the sensors. The ML algorithm can be applied on the different kinds of data stored on the cloud server to make a decision about when and how much amount of water is required for a particular crop, what is moisture label of the soil, how much manure is required when the crop needs seeding and harvesting, crop rotation, and so on [36].

Due to all this involvement of the (IoT) devices and the techniques of the ML for the decision making, further processing of data of the crops, soil, moisture, and temperature sensed by sensors helps in good crop production.

2.3.1 Internet of things devices used with machine learning in sustainable farming

The IoT devices used with ML in sustainable farming are as follows:

2.3.1.1 Precision farming

This farming practice is performed when it is required to grow crops in a more controlled and accurate manner. In this farming practice, a proper irrigation system and different IoT devices (e.g. sensors, actuators) are used. The crop metric services and products may include virtual optimizer, soil moisture sensors, and variable rate irrigation (VRI) optimization. VRI functionality can be used for the variability of soil, increase of water-use efficiency, and increase of agriculture yields.

2.3.1.2 Agricultural drones

The use of agricultural drones is very beneficial in agricultural practice. Through the GPS-based analysis, the drones work in the fields, and through the help of sensors, tracking of filed, embedded software they perform their function from time to time and analyze the whole condition of crops. The major benefits of drones are real-time monitoring of crops, spraying on crops, analyses of the agricultural field, health imaging of crops, and the potential to increase crop production.

2.3.1.3 Greenhouse automation

This IoT device is used for managing the water level and also analyzing the temperature of the field. It sends the data to the crop management system to take the necessary action. If the water level found on the field is less, then it activates the sprinkler drones for watering the crops.

2.3.1.4 Crop monitors

In this category, sensors are used to monitor weather conditions, soil health, crop health, soil moisture, temperature, and other various parameters. Based on the data received from sensors, farmers can take necessary action to cope up with the problem. The data can also be used by the farmers to analyze the best time for planting and harvesting the crops.

2.3.1.5 Climate monitor

In climate monitor, the smart sensors are used for forecasting the weather, and through the help of the embedded software, they analyze the whole condition and send the readymade details to farmers thereby avoiding crop loss.

2.3.2 Significance of Internet of things and machine learning in sustainable farming

The normal farming practices are not that fruitful, and it is not able to fulfill the requirement of the food as per the demand. The day-by-day growing population needs a productive technique of yielding by the help of which the demand for the nutrition-enriched crops is fulfilled. So, sustainable farming is an agricultural technique that meets the needs of the consumer, and it also fulfills the requirements of the nutrition by itself. In earlier farming practices, to produce high yields, the farmer used harmful fertilizers, excessive pesticides, and the artificial, or we can say totally chemical, manure. Due to this, the productivity of the field is increased for some time [21]. But on the other hand, the negative impact of that chemicals leave a bad impact on the whole future farming practice, which affects the fruitfulness of the soil, decreases the nutrition of food, and decreases the production of the crop so that it cannot fulfill the requirement of the growing population.

So, the IARI analyzed the whole condition of the present farming style, and it suggested the implementation of the new farming technique which is sustainable farming, and the government also promotes and launches new technologies and policies regarding this [37, 38]. One of the techniques of implementing sustainable farming is through the use of IoT and ML, which plays an imperative role in the development, monitoring, scaling, and analysis of the crops. The use of IoT and ML is to maintain the sustainability of the crop production with the help of the actuators and sensors, which sense the current situation of that particular field then send the data to the cloud where ML, which is a feed analyses the dataset and runs it on its algorithms with the help of which the decision making of the IoT devices are performed. Through all these operations, the sustainable farming performs very efficiently in low cost and avails more production through these farming practices and technologies. It also promotes the use of green manure, natural fertilizers, less use of pesticides, and the proper system of irrigation; through this, the local economy is also boosted.

2.4 Impact of sustainable farming on food security and economy

Sustainable farming means meeting society's present food and market needs, without compromising the quality of foods for current and future generations' need [39]. The motive of the World Food Summit is that food security exists when all people get sufficient food all the time which is nutrition enriched and fulfill the health requirement of the population for their active and healthy life. Nowadays, the degradation of lands is a major problem; this occurs due to the increasing population, excessive use of chemicals, and the avoidance of the traditional system for soil fertility. Due to continuous growth in population, there is a huge need to produce nutrition-enriched crops to fulfill hunger as well as to maintain the soil health by promoting the use of biofertilizers and green manure, and to control the use of irrigation as per the necessity [40]. By performing the traditional practices of farming, the fertility of the soil is decreasing day by day, and it is affecting the nutrition-enriched crops. Hence, it is becoming unable to fulfill the food needs of the growing population. And we know that the nation needs nutritious food for the future generation to make them healthier and stronger. Sustainable farming helps to yield highly nutritious food as per the demand of population, and it also promotes the local economy by the use of natural fertilizers and green manure in farming practices.

2.5 Conclusion

This chapter starts with the motivational significance of IoT and ML in sustainable farming. Here, the main focus is on smarter, efficient, and better crop-growing techniques that are required in order to meet the growing demand for nutrition-enriched foods of the increasing population for their healthy and active life. Further, the role of the agricultural sector has been discussed in the production of highly nutritious food for the growing population and economic growth for the country. IoT and ML play a vital role in detection and diagnosis of soil health, and help in temperature maintenance, improved techniques of irrigation systems to provide better production of crops, and maintain the fertility of the soil for a longer time by using biofertilizers and green manure. Different applications of IoT and the collaboration of ML decision-making abilities or challenges have been discussed in the chapter. A survey on soil health, humidity maintenance, irrigation systems, fertilizers, pesticides, and so on has been done using different IoT methods on various data sources, and in each survey IoT and ML have shown promising results as required. The implementation of new methods for production of nutritious crop yield and the new ideas is coming with the younger farmer who is performing agriculture as their profession the new innovative ideas are developing day by day through the help of which the better and efficient crop production is done in low cost. This idea of modernization of farming is straightforward, reasonable, and operable. In the earlier context, as per the survey and analysis of IoT and ML methods on different platforms, it is found that these methods have shown acceptable and promising results as the required and correct analysis of crops, and they increased the production rate with their different tools and techniques as compared to the existing traditional practices of farming.

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Jyoti Batra Arora

3 An innovative combination for new agritechnological era

Abstract: Emerging communication technologies have enormous potential to give a new wheel to development and to meet global competition. In the same line recently, a new era of Internet-connected sensory devices has begun. A report proclaimed that the number of interconnected sensory devices would be around 25 to 50 million in 2020. Internet-connected devices are also considered as the Internet of things (IoT), which provides a link between physical and cyberworlds. IoT is used in almost every sector such as smart cities, medicine, networking, and agriculture. In few IoT applications, analyzing power and smart processing of big data act as a catalyst for their development. Data science is a combination of machine learning (ML), artificial intelligence (AI), data mining, and other technologies that perform pattern analysis to enhance the intelligence of IoT services and applications. Technologies of data science along with IoT are mainly used in the area that works with volume, velocity, and pattern recognition. The biggest benefit of using ML with IoT is the automation of a colossal amount of generated and exchanged data. Because of the predictive analysis of ML software becomes able to predict incoming desired and undesired events. Therefore, the ML system is not only recognizing abnormal behavior but also helps in understanding and establishing long-term trends. No ML technology can do anything without human guidance and interaction. Continuous correction and supervision are required for effectiveness and efficiency in data analysis. Therefore, the interaction and involvement of AI are required. This chapter also discusses the same issues. The first section of the chapter provides a detailed description of ML and its relationship with IoT, and also explains the description of IoT architecture and different technologies of ML. The second section provides the different applications of IoT where ML helped to make the intelligent system. The third section describes the futuristic scope of IoT and ML, and how these two technologies help in different areas like smart cities, smart human, and smart farming. The chapter concludes with a summary of these technologies and the usage of these technologies to build smart applications and services. This chapter provides the answers to questions such as how the classification of ML techniques is being used in various IoT applications and services.

Keywords: machine learning, IoT, data analysis, data science

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https://doi.org/10.1515/9783110691276-003

3.1 Introduction

Internet of things (IoT) is a combination of various physical objects that are embedded with each other through electronics, software, and network connectivity. These devices are entitled to a small amount of storing computational and communication power. The “things” referred to in this chapter are all objects from our daily life such as meter, adapter, camera, refrigerator, and smoke detector. Novo et al. [1] defined IoT as a distributed network of an embedded and interconnected system of communicating devices through various communication technologies. IoT provides a huge range of services and applications covering all the domains ranging from infrastructure, retail, transportation, and personal healthcare [2]. IoT network brings challenges in maintaining these devices, storage, communication, and privacy. There is a huge range of research going on about architecture, communication and computation, security, and privacy of IoT [3].

IoT devices generate huge data that is used in pattern recognition, prediction analysis, and assessments. This data provides a different platform to process the data. A new mechanism is required to harness the value of IoT-generated data. The most suitable computational paradigm would be ML. This technology not only provides embedded intelligence to IoT devices but also infers the knowledge from device-generated data. Mahdavinejad et al. [4] poised that ML enhances the capability of these smart devices to understand or predict the situation. He also described the variation in behavior of these devices on knowledge of understanding the situation. ML can be used in classification, regression, and density estimation. ML techniques and algorithm anchorage in applications are based on IoT like speech recognition, malware detection, and fraud detection to provide intelligent services. The next section provides details of security issues and challenges in IoT applications.

3.2 Structure of IoT

IoT has given a new direction to research. The research in IoT has gained a lot of attention in terms of education, innovation, and money. The research is supported by academicians, industry people, and many standardized bodies such as telecommunication and semantic web. IoT is considered as the future of the Internet. IoT plays with data in a variation like may capture, and store the data. It may also share and communicate the data to and from the outside world. For this purpose, IoT requires applications, service platforms, and various products. IoT comprises various types of sensor devices, and these devices are connected with database tables through various programming languages. These databases store data from smart devices having sensors on them. This data may be analyzed using various algorithms and converted into machine knowledge. The whole process is done to enable machines a better understanding of the human world and can be represented as a knowledge hierarchy in figure 3.1.

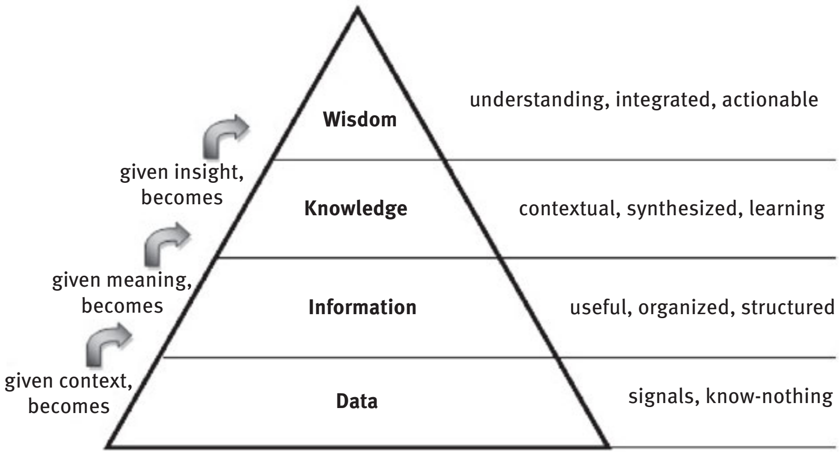

Figure 3.1: Knowledge hierarchy source [5].

The lowest layer represents the data produced by IoT devices. This data is basically in raw form, which is converted into structured information in the next layer. The second layer filters and summarizes data in machine-readable form. However, human and high level applications do not require information; rather, they need hidden knowledge behind this information for better understanding. This hidden knowledge concludes the wisdom at the end of the machine to forecast the future. A few services and products develop wisdom. The machines that are associated with IoT automatically summarized this knowledge hierarchy.

IoT has various technological issues associated with it, such as diversification and management of devices, and integration and interoperability of data received from various devices. As the number of devices attached in IoT is very large, their communication among themselves may give rise to many data linking issues. All the connected devices should have elastic topology for smooth communication among themselves. For example, if the front door is attached with sensors that are opened through remote, the command can be given through the light in front of the door.

It is the biggest challenge in IoT infrastructure to keep all devices working together. For example, in the case of smart grid application, a large number of sensors determine power consumptions from various organizations and corporate houses. In IoT applications, a huge amount of relative data is generated from various sources which may also enhance value to establish the connection between these data. The next challenge related to IoT applications and services is the velocity and volume of data and to manage the data on the scale. This is also one of the common problems faced by big data. As mentioned earlier, IoT applications require sensors and various devices that are evolving with new capabilities and improved functions. An ecosystem and platform are required to build compatibility with these new and innovative sensors or devices.

3.3 Security challenges in IoT application

IoT services and applications are complex in nature and contain integrative arrangements, hence, security and privacy become the major issues. Therefore, maintaining these issues in IoT services is very much challenging. IoT devices and the environment also pose some additional challenges. The security of IoT devices may include architectural security, data security, communication security, and malware analysis. Fernandes et al. [6] described the similarities and differences of security issues in relation to traditional IT and IoT devices. They stated software, hardware, network, and applications as the most common driving factors. It has been observed that there are fundamental similarities between IoT and the traditional IT domain. The data produced by IoT devices are more valuable for analysis to predict patterns, behavior, and future trends. The analytical result may help to understand the behavior of any individual and product, service, or application. This information becomes very useful to various policymakers to make changes in their products according to the preference of an individual. However, it may convert the IoT devices into eavesdropping devices, which can capture information like audio, fingerprints, and face recognition, thereby assisting in IoT device intrusion.

IoT services and applications are considered as boundaryless as these adjusted themselves continually whenever there is an addition of new devices or movement of the user. Hence, these parameters may cause the continued expansion of the attack surface of the IoT framework and introduce many new threats and vulnerabilities.

There arises a requirement of a cross-layer design and optimized algorithm as the solution to security and privacy issues of IoT. IoT devices may further require a new generation of the algorithm (cryptography) to overcome the issues related to privacy and security. A holistic privacy and security approach is more appreciated than an existing security solution. The number of IoT devices is directly proportionate to the challenges in the security mechanism. This new approach provides a new evolutionary, robust, scalable, and intelligent mechanism to cope with the challenges in privacy and security in IoT.

ML provides the optimal solution through learning either by using past experience or example data. Safavian defined the essence of ML as the following two basic classical definitions:

a. The development of computer models for learning processes that provide solutions to the problem of knowledge acquisition and enhance the performance of developed systems.
b. The adoption of computational methods for improving machine performance by detecting and describing consistencies and patterns in training data.

Xiao et al. [7] explained various ML methods to protect data security and privacy of IoT applications and services. The three challenges described them with respect to futuristic implementation of ML are partial state observations, overhead projection of communication, and computational and backup security solutions. ML through mathematical techniques builds the models of behavior and pattern recognition. ML enables the devices to learn without the use of distinctly programming. The futuristic prediction based on new input data can be easily done by the use of these models.

ML is having multidisciplinary nature that comprises AI, optimization theory, and cognitive sciences. It is very much useful in robotics and speech recognition where human expertise cannot be used and in problems whose solutions change with time. In real-life problems like analyzing the threat against mobile endpoints or applications, ML has gained a lot of success. For example, “Macie”, the service launched by Amazon, uses ML techniques to classify and sort data stored in cloud storage. Though the ML technique is very reliable, still sometimes it produces false-positive and true-negative results; hence, it requires proper guidance and modification. An advanced version of ML is deep learning (DL), which helps to overcome this issue and itself determines the accuracy of prediction. Mohammadi et al. [8] and Nguyen et al. [9] poised the suitability of DL in innovative IoT applications for prediction and classification tasks because of its self- service nature.

IoT network produces a huge amount of valuable data for analysis. ML and DL are important key components in building intelligent IoT systems and delivering smart services of IoT applications [10]. From the aforementioned example and research, it has been observed that both these can be used in IoT network for analysis of security, attack detection and prevention, and malware analysis. Verdouw et al. [11] described the challenges faced to deploy these models on resource-constrained IoT devices. The occurrence of these challenges is obvious as a necessity to reduce the storage and processing overhead of IoT devices. A cultivated security mechanism against malicious attacks is not feasible as IoT devices are resource constrained. The extensive deployment of IoT devices also increases the attack surface. Various communication technologies such as ZigBee, LoWPAN, z-Wavw, and NFC can also be used with various IoT devices. Chen et al. [12] described the limitations of these communication technologies, but these limitations are from a security point of view. Apart from the aforementioned challenges, few other challenges such as addressing, complexity, scalability, and insufficient resource utilization are also related to IoT devices and applications [13].

3.4 Existing ML-based solution to provide security in IoT

Various ML algorithms like supervised learning (SL), unsupervised learning, semi-supervised learning, and reinforcement learning (RL) can be used in IoT security. Sfar et al. [14] have described the thematic classification of this algorithm for IoT security.

SL is useful when from a certain set of inputs, specific targets are achieved. The labeling of data is done and then this labeled data has to undergo training to predict the belongingness of elements to a class. It is performed where both input data type and desired output are known. This algorithm is useful in areas like problems related to security and localization, channel estimation, spectrum sensing, and adaptive filtering. The most common techniques used in SL are classification and regression. The classification technique is used for prediction and modeling of available datasets and it produces discrete output, whereas the latter technique is used for prediction of continuous numeric variable and it produces continuous output. Logistic regression, support vector machine (SVM), and *k*-nearest neighbor are a few examples of classification techniques, whereas linear and polynomial regression, and support vector regression (SVR) are the useful algorithms of regression techniques. The only algorithm that can be used in both techniques is neural network.

Unlike SL, unsupervised learning does not work on labeled data. This technology works in an environment that provides input without desired targets. This technology works on unlabeled data and segregates them into different groups in a heuristic manner. This technology is very much useful in load balancing, cell clustering, detection of intrusion, and anomaly. The aforementioned techniques focus on data analysis, whereas RL emphasizes comparison and decision-making problems. RL trains the system where the system discovers its structure within raw data. The unsupervised group comprises clustering, where the degree of precision of predictive analysis is dependent on the previous usage of ML techniques to develop the model. The commonly used clustering techniques are hierarchical and *k*-means clustering. For various clusters, the *k*-means algorithm uses *k*-nodes as initial centroids. A distance function is used to label each node with its closest centroid. And to recompute the centroids, current node membership is required. If a valid convergence condition is achieved, it stops here; otherwise, it goes back to the previous step and restarts again. IoT applications generally come under the umbrella of unsupervised learning that has very basic information about the environment. Fig 3.2 presents various ML methods.

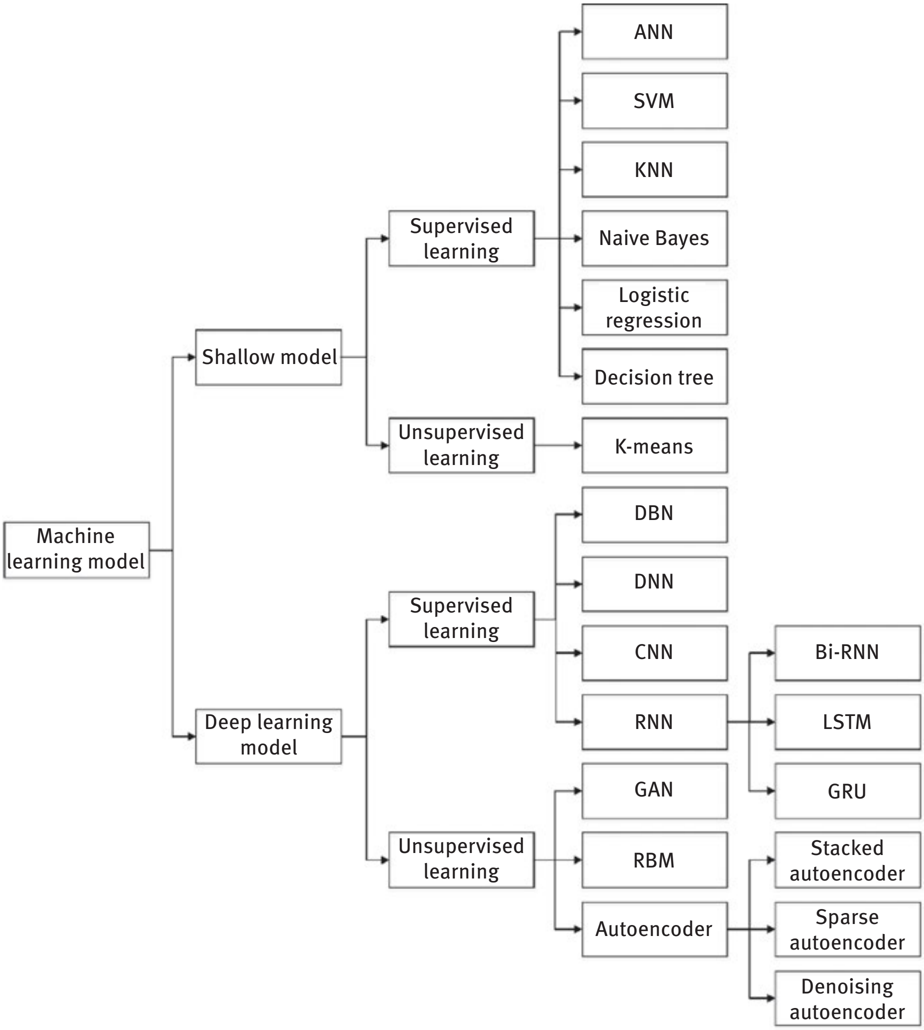

Figure 3.2: Machine learning and its types.

Semisupervised learning, as the name indicates, exists between supervised and unsupervised learning. The labeling cost is very high; moreover, it also requires human intervention to do the labeling. Semisupervised learning is useful where most of the observations do not have labels.

RL works where specific outcomes are not defined, and agents learn from feedback that they receive after interacting with environment. DL is most suitable for distributed computing, learning and analysis of absolute unlabeled, uncategorized, and unsupervised data. RL develops the reward and action relationship that helps in solving various IoT problems. The choice and categorization of various ML techniques are directly proportionate to the availability of data.

Lane et al. [15] poised that artificial neural network (ANN) develops DL, so learning follows repetitive adjustment of density among each pair of neurons. This technique is based on structure and functional aspect of human brain's neural networks. The computations are arranged in such manner to make an interconnected group of artificially designed neurons. It enables to process the information using the connectionist approach. The nonlinear statistical nature of neural networks is promptly used for data modeling. These are used to model complex relationships between input and output to find the pattern of data. DL develops a deep linking of the IoT services and applications. Wang et al. [16] stated that DL can be used in various applications like computer vision, speech recognition, and natural language processing through improved classification modeling. DL methods are also recognized as hierarchical learning methods as these are capable of capturing hierarchical representations in deep architecture. It basically works on estimation, function approximation, and the learning capabilities, and provides solutions to IoT especially in security and privacy issues. Chen et al. [12] explained various neural network techniques like recurrent neural network (RNN), convolutional neural network (CNN), deep autoencoders (AE), and generative adversarial network (GNN) as the potential DL methods to secure IoT services and applications. IoT devices are resource constraint so may not be capable to handle complex computational algorithm. Thus, DL algorithm is more preferred as it can perform better with low latency and complexity as compared to conventional techniques and theories [16].

Traditional RL is not capable enough; therefore, a combination of DL and RL is required to find the best policy to an action in a given state [17]. DL and RL are mutually benefitted. DL is more prone to misclassification; however, it is capable of learning from complex patterns [8]. S et al. [18] described the use of deep reinforcement learning (DRL) in "AlphaGo," an application developed by Google. DRL algorithm is used mostly in DDOS detection and security purpose in IoT networks.

DRL, as the name indicates, includes both RL and DL, which utilizes decision making of RL and perception of DL. DL integrates with prediction and classification and function approximation, and RL integrates with decision making, where a software agent learns to perform prime actions over various states by interacting with an environment. Both of these technologies work in conditions where dimensionality of data and states are very large. Traditional RL is not capable of security and policy; hence, a combination of DL and RL is required where agents do self-learning by interacting with the environment and developing suitable policy to get optimum rewards. Here, RL along with DL develops the best policy and performs various functions to develop a qualitative action for a specific state [19]. This algorithm is capable of learning anything from physical world without any crafting of features and also performs classification with DL.

A few more common ML techniques are described here that are used in IoT applications to analyze data and predict the best alternate solution in different industries and businesses. Inductive logic programming is one of the most useful techniques of ML, which is used to integrate the learning system with the help of logical programming as its representation for input examples, background knowledge, and hypotheses. If specific sets of examples with logical database of the facts are provided, the hypothesized logic program can be derived easily. Any type of negative instance is not accepted; rather, any kind of programming language for representation of hypothesis is accepted.

The other most commonly used probabilistic graphic model technique is Bayesian network, which uses a directed acyclic graph to represent a set of random variables with all their conditional independencies. It is useful in health monitoring system to represent the probabilistic relationship between various diseases and their symptoms.

ML uses decision tree as a predictive model to map the observations of an item to predict different conclusions on targeted value or output of the item. Decision trees may not provide the desired result in case of large databases; hence, association rule learning is used for discovering different interesting relations between all the variables. Each vertex demonstrates a feature, whereas each edge of the tree represents the value of vertex in classified samples [20]. This approach works on integration of two techniques: induction (building) and interference (classification). The decision tree is the most preferred collaborative classifier among other ML classifiers with respect to security applications like intrusion detection in IoT devices [21]. SVM is another method used for various security applications in IoT devices. SVM is a more efficient method as this method creates a hyperplane to make a division of data points in terms of space and time complexity [22, 23]. A study proposed by Ham et al. [24] described a system to detect malware in IoT applications and services and make the system secure. They have used a linear SVM to the proposed system and also given a comparison on performance of SVM with other detection techniques and ML algorithms. This technique is also very useful in research to exploit device security. It is a more effective methodology than the traditional method to break cryptographic devices.

For general classification in SL, *k*-nearest neighbors are used to classify the data sample on the basis of the labels of the nearby data samples. This algorithm differentiates the *k* kind of clusters to minimize the distance between them. However, being the simplest classification method, it can work effectively on large datasets. The nearest neighbor or node with best *k* value always has a variation in the value on the basis of dataset. The other classifier of SL is random forest, where several decision trees are developed and combined together to develop a robust prediction model to improve the results [25]. Though this classifier is developed by using decision trees, these classification algorithms substantially differ. Meidan et al. [26] poised the practical significance of random forest in correctly identifying unauthorized IoT devices.

Principal component analysis (PCA) the process to detect real-time systems in IoT applications and services. It also converts a large number of probably correlated features into a lesser number of uncorrelated features [27].

Most of the IoT services are based on data exchange techniques across various platforms. The generated data from IoT applications and services is analyzed using a DSS to make sense out of it. The data flows in similar manner in all of these processes, but processes may differ depending upon architecture of IoT. The authentication of user or application is required in case the user requires any data or application. It is the basic security requirement else it will deny the access request. Network and output access controls are also required which is also very cumbersome. ML-based access control mechanism is required to grant and revoke the access to specific users for any critical dataset of IoT.

3.5 Areas where ML is providing solution to IoT applications

IoT has touched every sector with its efficiency and ability to connect these sectors with each other. It has provided an intelligent system to people. In recent years, many new and different protocols and methods are invented by researchers to enhance the quality of life. IoT has a very big range of services and applications; hence, it becomes crucial to implement IoT in industry and research [28]. ML is the most preferred technology that works on a lot of applications with IoT in both research and industry. This section describes a few schemes from recent researches.

Ventura, in his paper, described the system of Arduino MEGA as the simplest method to implement ML algorithm with IoT to save the energy cost of the coffee machine. ML along with sensors is useful in traffic routing. The scholars in Milano by the use of LarKC platform designed a system to suggest various routes to a destination in case of any issue in traffic and weather. The proposed system uses an API named RESTful for transmission of request and respond message. This system performs path-finding and traffic prediction. This model is useful for predict the traffic during festive season.

IoT is also suitable for sustainable living. It is used to implement the light and humidity sensors. Sasidharany [29] suggested the future vision IoT application in making smart home or smart industry. A smart home may respond to the changes in climatic conditions or surrounding and climatic conditions like automatically switching on AC as per temperature of room and opening the main door of the home on the basis of face recognition of visitor [30].

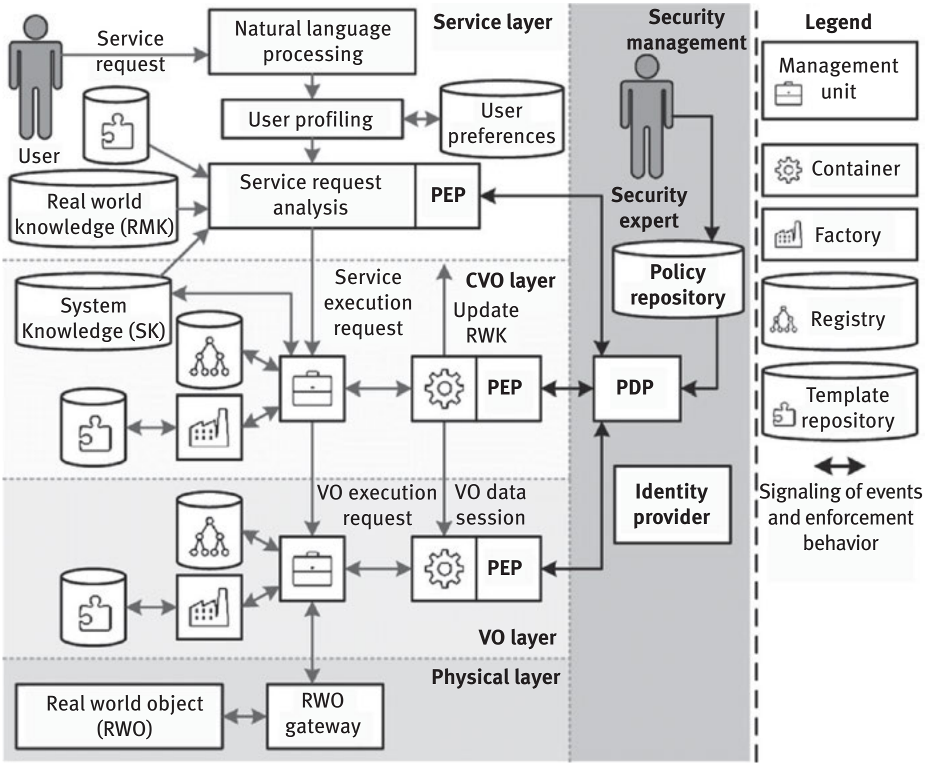

Figure 3.3: Architectural control flow of implemented functionalities (Swathya, 2014).

Figure 3.3 represents the IoT applications that may be suitable for home. It may be implemented in any apartment with light, humidity, and temperature sensor. For protection it may have heart rate sensors also. This process can be implemented using Java along with its library files to recognize framework and its functionalities. This process comprises different modules to analyze the request sent by service requestor and translate to produce the requirement of composite virtual object (CVO). A former request may arise a composite virtual object requirement that consists of temperature, humidity, and light sensors. Different sensors are required in different CVO environments. For example, to monitor health of an individual, CVO may require temperature and heart rate sensors. Similarly, for farming and emergency services, temperature, humidity, and pH-level sensors are required. The next level of CVO requires CVO management unit and CVO registry. After getting the service request, CVO management unit looks for CVO registry to fulfill the requested service. In case, the required CVO is unavailable, it also searches for relevant VO in the VO management unit to perform operation on service request. The VO after satisfying bought all constraints at one place to develop a CVO, that work on alone and independently on various operations on request. The captured data is analyzed at the real-world knowledge model layer and helps the system in decision making and prediction of futuristic behavior.

The combination of IoT and ML algorithm is used by many industries for utilities, healthcare, traffic, and development of new innovative products in manufacturing, transportation, retail, and so on. A huge amount of data is gathered from these machines and used in development of many applications. Utilities help in load balancing, dynamical allocation, and predicting the usage and dynamical allocation of resources to save energy. It can also be used with smart meter of gas, water, and electronic gadgets to gather the information about the previous usage of these machines.

In manufacturing unit, camera controller is used as IoT-enabled device to save the human resources. In the case of something going wrong, these camera controllers can make the alert either by alarm or by lighting. This type of fault prediction saves a lot of resources and money. Not only in the manufacturing unit, but IoT and ML are also useful in software and network industries. A few research schemes related to this field are discussed in this section.

A scheme is suggested that classifies and identifies the IoT devices in networks using SL method [26]. This scheme provides security and integrity to the network and its devices and ensures that IoT devices are connected to these devices in network. Another scheme was suggested by Ferdowsi et al. [31] for dynamic IoT watermarking. This technique was based on deep learning technology to identify cyberattacks.

IoT also worked in healthcare sectors. It helps to track the personal history of patients. Most of the IoT application in health sector is based on wearable devices. It helps to track the data of patients for detailed analysis of their health problems. Kumar et al. [32] provided models for blind people that help them to navigate freely anywhere indoors as well as outdoors. It is based on intelligent, self-contained navigation, and face recognition techniques. It used to provide them a hassle-free environment by avoiding all the obstacles in their path and also find the person in front of them.

IoT-based health monitoring system was proposed by Kumar et al. [32]. The proposed system has IoT-based sensor devices that collect the data from human body and use Amazon S3 services to predict various parameters like blood pressure, temperature, and heart rate of body.

IoT is not only used in the predictive analysis, but also to predict multilevel stress. This type of testing uses ECG signals with ML to identify the different types of stress faced by an individual. Similarly, Chen et al. [12] have given the health monitoring system using clothes. According to the Internet of Medical Things (IoMT) forecast, the devices of IoMT have captured 60% of the health and medical sector. IoT has a huge range of applications and services that generates optimum number of opportunities in health and medical sector [33].

Truong et al. [34] suggested a designer's scheme of IoT system containing environment data to cloud storage. This data is used with ML algorithm to predict future environmental conditions. It is a useful method to detect any kind of fungal infection in the crop/field.

Similarly, many researchers have proposed new innovative schemes for agriculture and farming. A scheme is proposed for small-scale farming to sense the properties of soil [35]. This scheme was based on image processing and uses Bayesian algorithm for estimation of soil condition. Jaishetty et al. also proposed a scheme for agriculture monitoring and controlling. It uses lightweight communication protocol MQTT-Message Queuing Telemetry Transport and performs predictive analysis to know about the future condition of the environment and soil. The analysis of data collected by various well-connected sensors provides real-time predictions like requirement of automatic irrigation, monitoring of soil constituents, and water quality. Sometimes it is also useful in monitoring pests and diseases of the crop.

The combination of IoT and ML is also useful in human behavior analysis. A scheme was suggested by Zhang et al. [36] for identification and estimation of social behavior of users which was based on DRL. By the use of genetic weighted *k*-means clustering, criminal behavior analysis can be performed to identify the criminal behavior of an individual based on their past records and behavior on social networks [37].

Anjomsha et al. [38] proposed a scheme to identify the social behavior of human beings. This scheme has an intelligent system that continuously identifies the user on social networks. It uses the behavior pattern to identify a specific user on social networks.

Using this sensing technology, many cities are on the path to be smart cities. In India, cities like Bangalore and Chennai are working on the same path. A scheme was proposed that develops a new protocol for addressing smart home for living [39]. They have given the name "wellness sensors network" to the protocol. This scheme proposed to provide a safer and intelligent environment to the living being.

Chin et al. [40] suggested a scheme using the combination of AI, IoT, and big data to provide more services to make a city a smart city. They have worked on various parameters such as temperature and rainfall distribution. This scheme defines the correlation between short cycling journey and weather conditions of the city. Devi and Neetha [41] proposed a scheme based on ML and IoT to provide smart city roads. The proposed scheme works on congestion prediction algorithm of ML.

The concept of smart city needs smart transportation also. The smart transportation aims to maintain a balance in the routine traffic of a city by processing the collected data from different sensors situated at various locations and implementing data fusion. The analytical result of this data fusion may provide smart choices to users [42]. Ahmed et al. [43] poised that data analytics done for smart transportation enhances shipment schedule, improvises delivery time, and advances road safety.

In retail industry, IoT allows the customers to buy what they want and also make them buy more. The sensors are placed in the store, and with the help of shopping app, the data is gathered using Internet to know the buying behavior of customers. In transportation industry, it is useful for efficient allocation of buses and other transport. It helps to make optimal usage of resources and lowers the cost of operation during the busy working days.

3.6 IoT in agriculture

Every successful business thrives by consistently making better decisions than its competitors, and the agriculture sector is not an exception to this. IoT is one of the most demanding technologies that can bring advancement and improvement in agriculture sector. This technology used various sensors that ensure real-time monitoring in agriculture sectors. It also uses sensors to detect pH level, humidity level, temperature level, and moisture level. It also uses certain sensors that also predict weather conditions. The data collected through different sensors is analyzed and that helps to take decision. These decisions enhance the quality and quantity of agriculture. This analyzed data promotes new advanced techniques and real-time mechanisms like monitoring of water quality, soil constitutes, pest, and diseases related to crop [44]. IoT technology uses various sensors like spO_2, ECG sensor, airflow sensor, temperature sensor, sphygmomanometer, body position sensors, galvanic skin response sensor, and EMG sensor to predict the different environmental prediction to be used in agriculture factor.

By applying ML techniques and algorithm to the collected data, a new direction to development is provided to field management systems and AI-based real-time programs. ML and AL comprise various applications and analytical tools that enable the better decision, enhance the efficiency, and reduce the waste materials. This combination also helps to improve the production and manages the field by minimizing negative environmental consequences. These programs provide insights for farmer's decision support and action. The aforementioned ML techniques help in agriculture sectors in various areas. The separate description of each methodology is not in the scope of this chapter, yet it provides details of various applications of ML and IoT in agriculture. A study by Amateya et al. [45] poised the usage of ML in yield management. They worked in coffee field and developed a machine vision system to catch cherries and to shake them to prepare a well coffee bean during harvesting. A study by Ali et al. [46] described the model to estimate the grassland biomass. This model works on the multitemporal remote sensing data and ANN. Pantazi et al. [47] also in their study demonstrated the changes in yield prediction. Their study was based on prediction of wheat yield. ML algorithms along with various IoT sensors provide the exact detection of weeds and their discrimination. It provides the low-cost weed detection without any environmental issues. A study provided by Pantazi et al. [48] poised a method based on ANN that captures multispectral images for identification of weeds that are hard to remove from field and cause huge loss in yield and to farmers. The image processing application based on ML enhances the trust of farmers on digital tools to recognize species of weeds and to determine the healthier crop from the infected one. A study by Binch and Fox [49] has described SVN-based weed detection method in grassland cropping. Irrigation is one of the important attributes of crop management as it is not an easy task. The forecasting of irrigation required depends on weather conditions. It helps to develop automated irrigation systems that help to maintain required soil conditions to enhance yield production. It would be helpful in the region where water conditions are crucial, and provides freshwater consumption statics. For a healthier crop, notification of daily dew point temperature is also required. It is considered as a special element to identify the accurate weather phenomenon and estimation of evapotranspiration and evaporation. A study by Mohammadi [50] predicted a model to estimate the daily dew temperature. This study also uses ML algorithms and techniques. They have collected the data from two different weather stations. In one more study by Mehdizadeh et al. [51], the researcher has given a model that provides the mathematical calculation to estimate monthly mean evapotranspiration. The study was based on various arid and non-arid regions. Another study by Johann et al. [52] discussed an innovative method to estimate soil moisture. This method is based on ANN model to process the data of force sensors located on a no-till chisel opener.

IoT and ML techniques might improve the weed detection and their discrimination without any environmental issues and side effects. Not only in detection of weed and yield management, but ML also helps in crop quality. Conventional methods to monitor the health of crops are very time consuming. Different agricultural organizations and farmers at individual levels are adopting the various intelligent techniques to monitor, detect, and analyze their fields' data related to status and feasibility of growing various types of crops. A study by Maione et al. [53] presented a model to predict and classify the geographical origin of rice samples. This study is based on the chemical component of rice. ML with conjunction of IoT helps to predict various attributes of soil such as soil drying, conditions, temperature, and moisture. The accurate estimation of various attributes determines soil conditions which may enhance soil management. The study performed by Coopersmith et al. [54] generates the method to evaluate the condition of soil drying that can be useful for agricultural planning. Nahvi et al. [55] developed a model that provides the weather data on daily basis for estimation of soil temperature. This study was performed in various regions of Iran, Kerman, and Bander Abbas with different climate conditions.

IoT uses various sensors to predict various environmental and soil attributes. Using various ML techniques on these IoT sensor data has given a new direction to field management. The combination of these two technologies may drive robots that may destroy or kill the weeds. It will also minimize the need for herbicides and pesticides. The data is recorded through various sensors and analyzed using various automated techniques of ML. The first step in processing the data collected manually from sensor data, based on timestamp, resulting in an augmented dataset. The next step is to analyze this data using various ML techniques that may help in decision making. The field management systems are evolving into real AI-based systems. This AI-based system provides a higher suggestion and insights for decision making regarding farm and yield management. This leads to improvement in production and quality of crops. It is also expected that in future, ML techniques can be used as a more integrated tool to improve the quality and quantity of various crops in different weather conditions. Using ML techniques may provide knowledge-based agriculture that may increase production and quality of crops. The other emerging field in the agriculture sector is "digital farming," which is preferred to use to increase the crop production by providing decisions related to key farm management with data-driven insight. Farmers need to take several critical decisions that may be complex and interconnected. These decisions may have positive or negative impact on their risks, sustainability and return on investment. ML and AI would radically improve the way farmers contribute to yield production as well as in biofuel industries.

3.7 Limitation of using ML in IoT

There are certain inherent uncertainties associated with IoT data that require considerable modification; however, ML technologies are not efficient enough for this [56]. Therefore, a few limitations or challenges are also associated while using ML in IoT. The algorithms of ML possess issues with memory and computational complexity. ML techniques lack in scalability; hence it is only limited to low-dimensional problem. ML works on constant stream of data in real time so sometimes it is not suitable for smart IoT devices that work on real-time data processing.

The other biggest challenge while using ML/DL in IoT services is to develop or extract a real-time based or super quality training dataset that may have the detail of possible types of attacks. As mentioned earlier, IoT devices generate huge volumes of data; therefore, realistic streaming of data and its maintenance is always challenging in this process.

Heureux [57] discussed the reverse proportionate relationship between the dimensionality of data and predictive ability of an algorithm. IoT network generates diversified data that differ in semantics and format, hence, exhibit syntactic and semantic heterogeneity which raises a problematic issue to ML [58].

In the case of ML, statistical properties of entire dataset remain the same; therefore, in real-time applications where data from different objects have variation in representations and formatting-related problems for ML algorithms, these algorithms are not efficient to work on semantic and syntactic diversified data. Merging of ML algorithm with existing streaming solutions enhances the overall complexity of an algorithm.

IoT services may have possibility of high noise and corruption of data as data streaming is very high, and devices and objects are connected heterogeneously. So, for secure IoT system, effective and multimodal DL model is required to handle low-quality data [59]. The accuracy of ML/DL is directly proportional to size of dataset, that is, richer the dataset, the more accurate the ML/DL. It is a cumbersome task to generate a large dataset for ML algorithms to work on data privacy and security in IoT systems [60]. It is desirable to find the alternative methods to acquire optimal data. Data augmentation technique is useful in producing new samples from the existing ones.

Zheng [61] discussed the performance of ML and DL algorithms in relation to analytical power to learn variation in behavior whenever there is an interaction between IoT devices in heterogeneous ecosystems. However, potential of these technologies to predict new attacks is simply based on derivation and mutation of earlier attacks; so, advancement in IoT security system is required to generate a secure communication between devices enabled with DL methods.

Pan and Yang [62] have given the concept of transfer learning. They poised that this learning comprises transfer of knowledge from a domain having ample amount of training data to a domain with insufficient training data. The transfer learning aims to make reduction in time and effort needed for new learning process. However, if this learning is cultivated successfully from IoT elements, it can improvise security performance of IoT system with low cost and effort.

3.8 Futuristic scope of IoT and ML

ML is the driving factor for AI. The major advantages of using MLsystem are heuristic learning, decision tree for fundamental administration, and data acquisition [63]. All data science-based applications like data mining, information retrieval system, search engine, and big data analysis use ML algorithms. It also helps to find applications in computer vision for object identification [64]. IoT is the most used and recent application of ML. Many researchers presented the survey using IoT with ML in different applications and services. Kumar et al. [65] presented the survey of IoT and its application in-built engineering. Buczak and Guven [66] have given the survey on IoT in cybersecurity system using data mining techniques. The main issue in using data augmentation is to produce new data samples so that data distribution for each class can be preserved. Therefore, the futuristic scope says that a suitable method for data augmentation might be developed to improvise the taxonomical accuracy of various learning methods.

ML algorithms and techniques have an objective to develop contextual awareness and intelligence to various devices and objects; therefore, these technologies can weaken security trade-off issues than traditional access control methods. The required level of security and its framework should exhilarate different operation modes of a specific application. It can be a new research area to make optimal utilization of intelligence and power. It can also be a research topic of how ML and DL satisfy different security trade-off effectively under various operation modes within special areas and applications.

ML and DL techniques along with their algorithms contribute effectively and potentially to secure the amalgamation of social networking with IoT networks. This research area is in its infant stage and requires a high-speed investigation and development. Hitaj et al. [67] poised that DL techniques and its algorithms are prone to potential attacks while acquiring the training data. Any attacker can easily build DL system. This system may easily recognize the working of DL-based detection methods to mitigate the attacks. These attacks are not easily traceable. This area also needs more research to predict the appropriate alternative to solve this issue.

3.9 Conclusion

ML techniques are being used to make IoT devices and applications more smart and intelligent. ML techniques can be used to determine the behavior pattern of any system; hence, it is very much useful in quality of crop and detection of weeds and infected plants within the crop. ML techniques help to reduce computational cost, and enhanced computing power and assimilation of different technological breakthroughs have made it a success. ML creates models that train, test, and design the datasets. DL and ML algorithms are used in pattern detection and similarities and variations in dataset, yet the fundamental disadvantage is that it generally requires a dataset to perform learning, and then the learned model is used in the real dataset. DL helps to overcome the limitations of ML and is used in industry domain. Microsoft's Cortana, Apple's Siri, Google photo, and Amazon's Alexa are well-known examples of DL algorithm. DL, RL, and DRL are having a prominent place in research area to learn automated extraction of huge volumes of high-dimensional unsupervised data. These technologies are assumed as very efficient techniques that are useful in prediction and classification in many applications. However, these may not be able to cater to all challenges faced by the IoT network. ML-based analytical techniques and tools offer security solutions based on behavioral patterns of the local environment by sharing the metadata with cloud operators.

After reviewing different papers, it has been observed that ML with IoT reduces the burden of people in their daily life by providing them intelligent system.

After analyzing different papers, the author came to know that most of the research is done in agriculture, social network, and human health, while more research is required in smart industry or home and wildlife area. ML and DL technologies develop intelligence to various systems to detect abnormal behavior of an object. Hence, an automatic response is generated at the infant stage.

Agriculture is one of the main industries and foundation stones in the economic development of a country especially in case of developing countries like India. The US Environmental Protection Agency predicted that in annual revenue to the economy of country, this sector contributed $330 billion (approx.). The various attributes like climatic change, increase in demand of customers due to rapid growth of population, and scarcity of food have propelled the agriculture sector to look into more advance and innovative approaches to improvise and protect crop yield. AI is playing an important role in that; however, IoT and ML have also joined this combination. This chapter has presented the role of IoT and ML in various sectors and how this combination has given a new direction to technological evolution. A phase of this chapter is also dedicated to usage of the combination of these technologies in agriculture.

Every scheme may be advantageous at one position and may have limitations at another end. By this chapter, the author tries to provide the description of various aspects of ML with IoT in different areas or sectors. There is a huge scope for researchers to explore the combination of these two technologies along with other related technologies.

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4 Recent advancements and challenges of artificial intelligence and IoT in agriculture

Abstract: Agriculture is an important and foremost sector in any country, especially in developing countries like India. The major income depends on this sector more than any other sector. Agricultural yield primarily depends on soil properties and irrigation water. Many times traditional farming based on old methods fails to give better yield. The advancement in technology should be utilized for better land productivity and to understand various aspects of the agriculture field. Internet of things (IoT) influences common man's life by making almost each and every field smart and intelligent. The IoT along with machine learning (ML) can play a very promising role for the betterment of the agriculture sector.

This chapter highlights recent state-of-the-art work done with IoT and ML in the agriculture field and the challenges of respective technologies in this sector. Agricultural automation can help with effective yield and may reduce human interference.

IoT is being used, nowadays, in different sectors. On the opposite side ML the application of artificial intelligence, provides the system the power to learn automatically and improve from experience. ML along with IoT can play a very promising role in the agriculture domain to study different parameters related to farming. The parameters may include soil parameters like soil pH, soil moisture, humidity, temperature, and weather and irrigation parameters.

Keywords: Internet of things, machine learning, agriculture, smart farming

4.1 Introduction

Smart agriculture consists of agricultural practices with the support of modern and innovative technologies for better and effective yield, which offers efficient results in managing, cultivating, and harvesting of crops along with analysis of various parameters related to farming. It has been recognized as an application of information and communication technology (ICT) in the field of agriculture. Smart agriculture is gaining massive popularity in recent years due to the improved promising income margins obtained from the agriculture field [1].

Soil properties and irrigation water systems must be better managed so that more productive and resilient agriculture can be achieved. Precision types of devices like

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https://doi.org/10.1515/9783110691276-004

Internet of thing (IoT) modules, sensors and actuators, automated hardware, robotics, and autonomous vehicles play a significant role in this field by helping farmers to boost production and harvesting crops in less time duration. This should comprise more practices that will ensure positive benefits such as lesser soil erosion, improved soil water retention, increased soil organic matter accumulation, crop health, and better crop productivity [2, 3]. These practices ultimately benefit agriculture economic growth, since better quality yield is achieved and better environment too. Smart agriculture can help reduce greenhouse emissions to a significant extent. Smart agriculture helps in the collection of information from the agriland and then carries out the analysis thereon, so that the farmer can make exact and valid decisions in order to grow top-quality crops. The data collection is completed with the assistance of sensors, cameras, microcontrollers, and actuators. All the collected data gets transferred to farmers or operators through the Internet for decision-making purposes [4, 5].

The modern ICT-based agriculture methods recognize, manage, and analyze inconsistency in fields by conducting crop production at the exact place and time and in the proper way for best profitability, sustainability, and security of the land resource [2]. Smart agriculture assures benefits from the perspective of agronomical, technical, environmental, and economic development. Hence, smart agriculture aims to reduce the heavy workload of the farmworkers, ultimately improving their quality of life [6]. Some of the application areas for smart agriculture are listed in Figure 4.1.

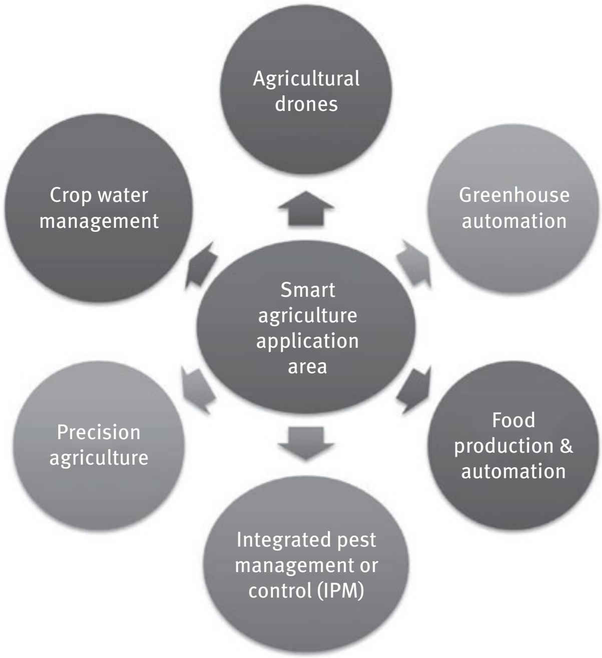

Figure 4.1: Application area of smart agriculture.

4.1.1 Introduction to IoT and ML in agriculture

Every field uses technology efficiently to get accuracy in work and to save time though farmers are using manual methods for their activities like crop monitoring, disease detection, and many more. To overcome the disadvantage of this manual work, many technologies worked previously like wireless sensor networks (WSN) and GSM networks with their outcome. But today, IoT is a popular network, which can make any physical things talk to each other. It is important to understand how this technology helps the farmer who takes care of the survival of our various societies. IoT works effectively with other technologies to get better outcomes like artificial intelligence (AI), machine learning (ML), and deep learning [2, 7].

To design any IoT system in the agriculture domain, many sensors are required to collect real-time data and to take specific actions. Large and complex data is produced by these application areas. However, this data comes from sensor devices which are of different types, different sizes, different significances, that is, this data is heterogeneous in nature and s very big. Therefore, to collect and analyze useful information from this huge data collected in real time with accuracy and within less time is very important [8–11]. Many researchers who designed smart agriculture systems tried to make their system intelligent from decision, time, and processing point of view. Basically, any automation system like smart city, smart home, smart hospital, and smart agriculture need to be intelligent. AI is an area of computer science, which is able to do work based on ML, deep learning, convolutional neural network, artificial neural network, and so on [12, 13].

IoT works on "connecting devices," ML works on "Connecting Intelligence"; hence, both combine to work for very efficient outcomes of "connecting intelligent devices" [12]. Figure 4.2 speaks about the growth of IoT and ML in agriculture research work done during the last 10 years according to the Google Scholar database.

ML is basically a type of AI which provides capability to learn from experience of machines. In real-time data analysis, ML algorithms take better decisions and appropriate actions without human involvement. ML experiments used by Arthur Samuel earlier in machines are used currently in the field of agriculture. To raise accuracy and to find accurate solution, ML is used in the fastest growing area of agriculture [14, 15].

ML model performance goes on increasing with experience gained over time. Various mathematical and statistical models are applied to trained dataset using ML algorithms [16]. After the learning process, trained model is used to predict and classify the desired output. Depending upon the learning type and learning model, ML can be classified as shown in Figure 4.3. Some of the example applications for these ML algorithms used in the literature [14, 16] by researchers are listed in Table 4.1.

The best popular application of ML in agriculture is agriculture drones/robots. Various companies are now designing agricultural robots, unmanned vehicles to

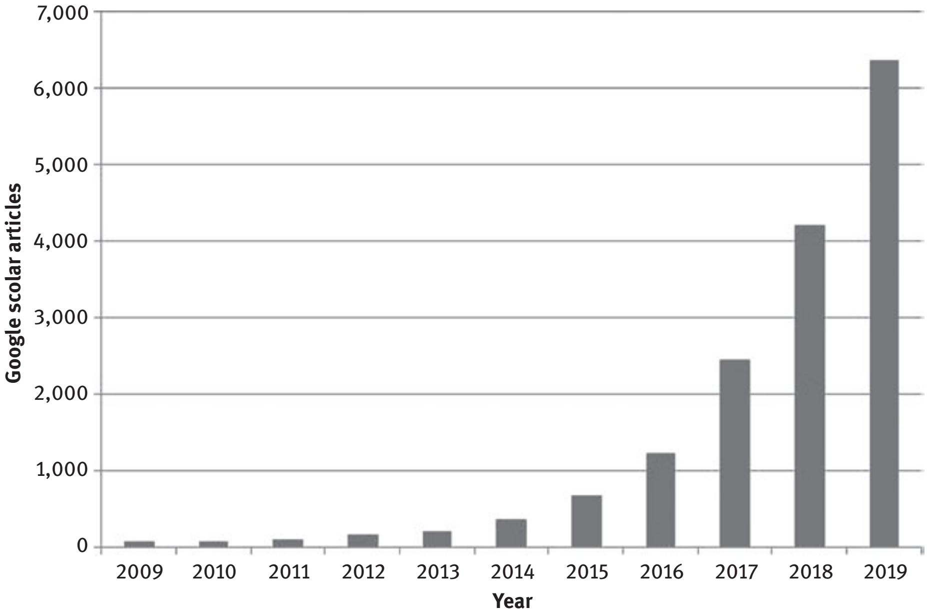

Figure 4.2: Growth of IoT and machine learning.

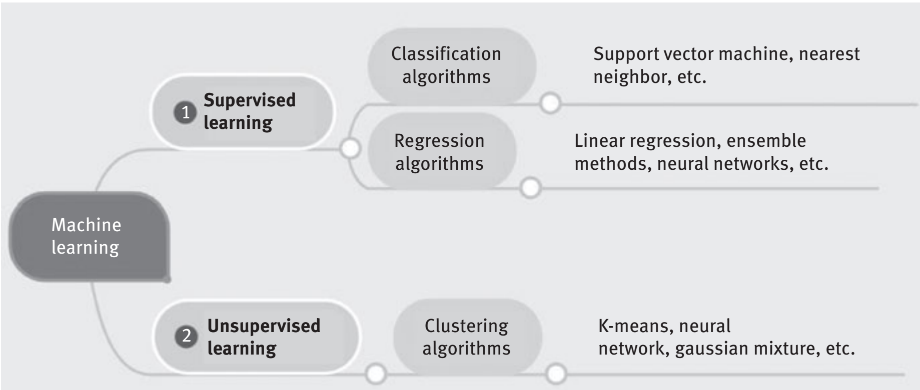

Figure 4.3: Classification of machine learning algorithms.

perform particular task related to agriculture, they are also using these algorithms to control the productiveness of soil. Farmers are now taking advantage of innovations in ML and deep learning technologies with IoT. A farmer also uses ML and the systematic tools to determine results of data on pricing.

Table 4.1: Example applications of machine learning algorithm.

Name of algorithm	Application
Support vector machine, linear regression	Count coffee fruits on branch, calculate weight of coffee fruits
	Estimate growing conditions of roses in greenhouse
	Predict temperature and humidity in greenhouse environment
	Predict the development stages of rice
Fuzzy logic	Predict the type of crop grown from soil pH, temperature, and humidity
Neural network, artificial neural network	Predict wheat yield
	Assess agriculture land suitability
k-Nearest neighbor	Predict occurrences of plant disease

4.1.2 Benefits of using IoT in agriculture

Farming is one of the most important areas for the development of any rising nation. India is recognized as an agricultural country for its significant agricultural fields and all other capitals associated with it. In recent days, many factors such as temperature, soil moisture, weather conditions, and irrigation systems are affecting the growth of agriculture which finally impacts productivity and yield production. Issues that arise due to these factors are becoming barriers for development of the nation. The agriculture sector needs some modernization in standard techniques that are being used currently in this area. New trends need to be implemented in agriculture which will be helpful to overcome all these barriers and better yield will be obtained. For many years, WSN has been used for smart agriculture. However, with the recent advancement in the field of Internet, there has been a remarkable shift from the WSN for smart agriculture to IoT as the major driver of smart agriculture [17]. This recent advancement in the field of the Internet is termed as IoT. The IoT integrates different technologies that already exist, such as WSN, cloud computing, RF identification, middleware systems, and end-user applications [17].

The interconnection of physical objects connected to communicate through the Internet is termed as the IoT. In IoT, physical objects are made smarter with sensing, actuating, and computing power [18]. With the proper integration of decision tools and automation systems, IoT may lead to empowerment of farmers. The main function of IoT in agriculture is to create a circle of monitoring, decision making, and action taking into the farming process. Application of IoT in the arena of agriculture mentions the use of cameras, automation systems, sensors, and other devices to turn each component and action in farming system into data. The sensors used in agricultural IoT application help in monitoring and measuring different parameters related to farming that affect the production and its associated processes. Table 4.2 summarizes the use of various sensors in agriculture with their functionality.

Table 4.2: Functionality of various agriculture sensors.

Sensors	Functions
Dielectric soil moisture sensors	They measure moisture levels based on the content of moisture in the soil.
Mechanical sensors	They evaluate soil compaction proportional to the various level of compaction.
Electrochemical sensors	These sensors help to collect, process, and map soil's chemical data.
Optical sensors	These sensors utilize light to measure soil properties.
Electronic sensors	These sensors are used to check farming if automatic equipment works.
Airflow sensors	These sensors are used to measure the permeability of soil air.

There are many benefits of using IoT in agriculture. This section sheds light on key benefits of IoT in agricultural field [13, 16, 19–21].

1. **Excelled efficiency**: Since the majority of population is dependent on agriculture and agricultural products, agriculture is in a race nowadays. Farmers have to grow more yield in deteriorated soil health, declined land availability, fluctuations in weather conditions, and unpredictable market conditions. Implementation of IoT in agriculture allows farmers to maintain and monitor products and conditions in real time. With the help of different sensors used in agricultural IoT system, farmers get deeper insight, and it becomes easier for them to predict any issues before it actually happens and takes corrective actions.
2. **Chemical-free process:** Deployment of IoT in agriculture allows sensors to collect massive agriculture-related data which includes crop disease and production process data. This helps to scale down excess use of pesticides and chemical farming. This approach leads to more cleaner and chemical-free products as compared to old methods of farming.
3. **Resource optimization:** Land, water, and energy sources are basic resources needed for farming. Optimizing these resources is the main focus of IoT in agriculture. Precision farming using IoT is dependent on data gathered from vivid field sensors that help farmers to make efficient use of available resources for better yield [14].
4. **Increased quickness:** The use of IoT in agriculture results in quicker processes. Real-time monitoring and prediction system allows farmers to respond

to change in weather conditions, any noticeable change in crop and soil health, and take appropriate actions. At extreme weather change conditions, agricultural professionals can save crops with the help of new capabilities.

5. **Increased production rate:** Requirement of food goes on increasing with the increasing population. The huge demand for food will arise when the population is increased up to 9 billion by 2050. IoT-based farming solutions such as hydroponic systems and IoT-enabled greenhouses facilitate short food supply chain and should be able to provide a fresh yield to the society. With the help of IoT-based smart agricultural systems, it is possible to grow food almost everywhere.
6. **Enriched food quality:** The deployment of IoT in agriculture field, which is completely data driven, not only allows growing food at higher production rate but also ensures that better quality of food products are grown. With the help of different sensors, agricultural drones, and automated systems farmers better understand the impact of different conditions on quality of food products. By using such systems, farmers can create suitable conditions to enhance nutritional values of the products.
7. **Wealth creation and distribution:** New business models shall emerge with the use of agricultural IoT, where farmers can directly deal with end users and consumers avoiding extra costing of “middle men.” This helps farmers in easy distribution and to earn extra bit of profit.
8. **Time management and cost reduction:** Another important advantage of using this technology is to get effective time management and cost reduction. Inspecting larger fields takes more time, and remote monitoring of IoT technology helps to save time. The ability to know when and where to apply pesticides will further help in cost reduction and excess wastage of pesticides.
9. **Expert guidance:** Increased use of IoT in agriculture domain shall promote services that allow the farmers community to have common data storage, share data and information, and increase interaction between agricultural experts and farmers. Farmers can thus take timely, effective, and accurate actions for better yield.

4.2 IoT in agriculture: use cases

4.2.1 Key drivers of IoT in agriculture

There are various factors because of which growth of IoT in agriculture market is tremendously increasing not only in India but across the world. One of which is higher demand for food across the world as population is increasing, which ultimately requires mass food production and effective manufacturing practices. With food crop production, gum, rubber, and cotton crop production is equally important, and it contributes to the national economy. Another one is unexpected changes in the climate which hampers the amount and quality of food across the world. Also, farmers adapted advanced technologies like IoT and AI, and some of them started to use applications for plant diseases and observation of livestock to improve efficiency [22]. Some of the main key drivers of IoT in agriculture are listed in Figure 4.4.

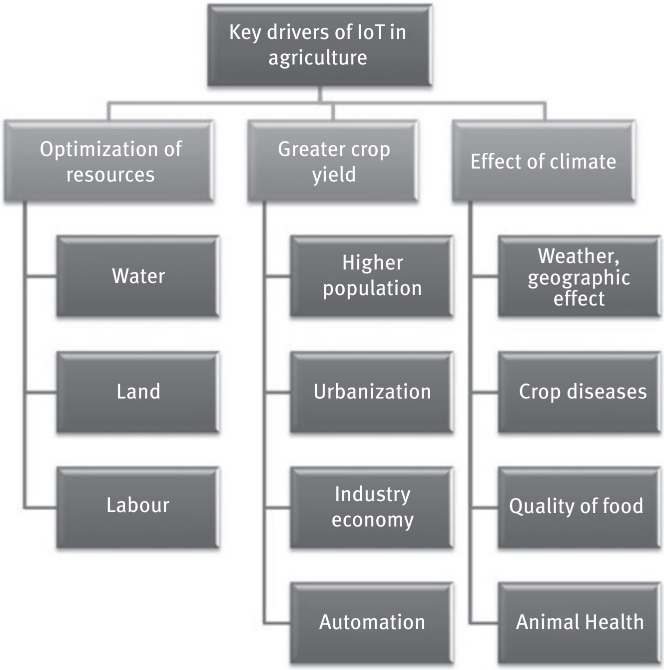

Figure 4.4: Key drivers of IoT in agriculture.

4.2.2 Smart agriculture using IoT

Most of all applications in the field of smart agriculture consist of the general working layers as shown in Figure 4.5. Selection of components at each layer can be done based on the need for application in a specific area and also based on accuracy, efficiency, and cost requirement.

The next part of this chapter discusses some of the use cases of smart agriculture using IoT.

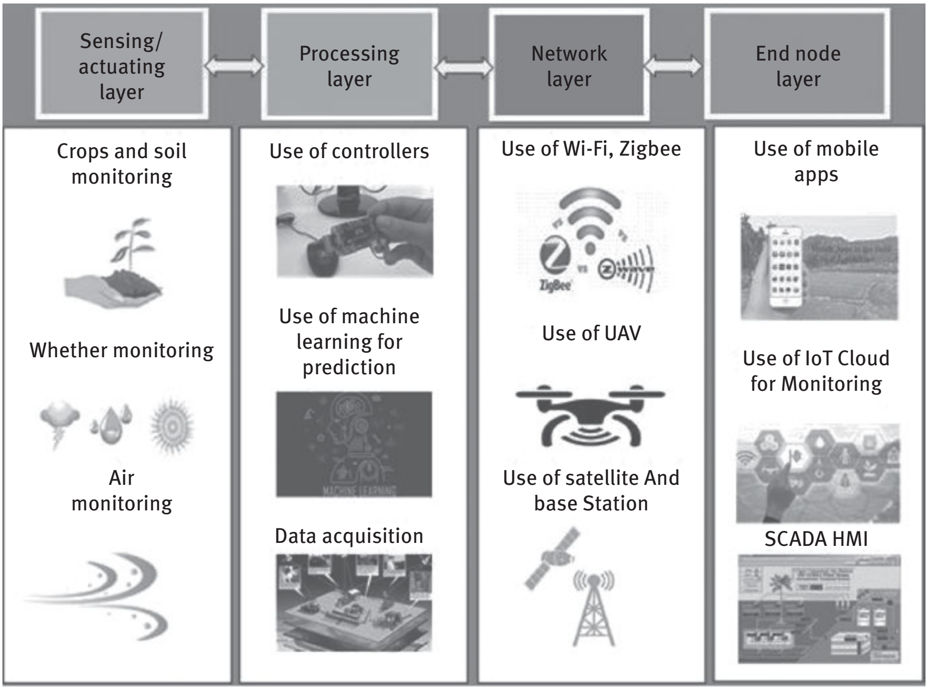

Figure 4.5: End-to-end working layers of smart agriculture.

4.2.2.1 Precision agriculture

We are aware that weather conditions and other dynamic data inputs can affect the productivity of the crop to more extent. Precision agriculture (PA) ensures precise and effective communication of real-time data to farmers, which is related to agriculture processes like weather estimates and soil quality. PA system observes, measures, and responds to variability in crops. The main goal of such a system is to design a decision support system for the management of a farm which enhances profits on inputs while conserving resources. Some important points about PA system are as follows [23, 24]:

- PA system involves nearby and remote sensing of sensors with the help of IoT.
- PA system comprises large amount of crop health data acquisition and processing which monitors state of the crop at various growth levels.
- Various parameters like water level, temperature, soil nutrients, and chlorophyll content in plant are involved in plant health.
- PA system designed with IoT informs farmers about which parameters are required for healthy crop, and where and how many amounts of these parameters are needed at a certain instant of time.

Increasing trends in PA are because of the acceptance of access to technologies like mobile devices, satellites, and speedy Internet. PA is one of the prominent applications of IoT [25]. The use of IoT in precision farming involves data sensing, data analysis, and evaluation of required reaction. Sensor integration, automatic control, information processing, and communication are the different processes involved in IoT-based PA systems. Here, different ML algorithms are used to analyze the sensor, and prediction is made using a trained dataset [17, 26].

Crop metrics is an organization that focuses on PA. They provide accurate irrigation solutions for a farmer enhancing returns and increases water, nutrient, and energy use efficiency. Crop metrics include the following products and services [17]:

1. Variable rate irrigation optimization: It improves effectiveness on watered crop arenas with structure or soil changeability, improves profits, and increases the efficiency of water use.
2. Soil moisture probes: This technology provides complete in-season native agronomy support, and sanctions to enhance water use efficiency.
3. Virtual optimizer PRO: This service is used for water management, which combines several technologies into one. This cloud-based service is designed for farmers and consultants to take benefits in precision irrigation by simplified interface.

PA is made more effective by the use of aerial- and ground-based vehicles named as drones.

4.2.2.2 Agricultural drones

Very advanced use of IoT technology in agriculture is the use of agricultural drones. Drones are very useful to farmers in saving their efforts and time. They provide graphical and aerial maps about the various crops on the farm. Drones help farmers to evaluate which plant needs immediate attention, current health state of plant, details of irrigation, observing progress of plant, planting procedure of crops, and so on. Drones have given high growth to agriculture industry because of their real-time data collection and processing strategy, high accuracy, efficiency, and capacity to overcome various obstacles [27]. Different concepts of IoT can be integrated into drones to increase growth of agriculture industry. Drones provide farmers with more accurate sensor data through the analysis of high-resolution images; they are easy to operate by farmers [12]. Few benefits of drones are:

- Drones are an inexpensive investment compared to most other farm tools
- Drones give much higher resolution data of crop situations to get details of crop
- Drones help farmers by getting yield potential, detecting leakage, detecting crop pests, and so on.
- Drones give an accurate count of plant growth so that farmer can purchase insurance, plan labors, and so on.

A list of some of the companies that provide solutions related to agriculture drone, its sensors' options, and software options is given in Table 4.3.

Table 4.3: Details of companies that provide agricultural drone services.

S. no.	Company name	Country	Link for details
1	Pigeon innovative	Mumbai, India	https://pigeonis.in/
2	ARIES solutions	Hyderabad, India	www.ariessol.com/
3	Dronitech	Mumbai, India	www.dronitech.com/
4	Aerobotics	South Africa	www.aerobotics.com/
5	AgEagle	Neodesha, United States	www.ageagle.com/
6	American Robotics	Cambridge, United States	www.american-robotics.com/
7	PrecisionHawk	Raleigh, United States	www.precisionhawk.com/
8	SenseFly	Cheseaux-sur-Lausanne, Switzerland	www.sensefly.com/
9	Sentera	Richfield, United States	https://sentera.com/
10	Skycision	Pittsburgh, United States	www.skycision.com/

4.2.2.3 Livestock monitoring

The health of animals is very important to the farmer, as a farmer may lose profit earned every year because of illness of animals. IoT-based livestock monitoring helps to track health of animals using IoT devices and can be monitored for any type of disease sign. The sensors in IoT device which are connected to the animals collect data about the place and wellness [22, 28]. Sensors can even track the pregnancies of cattle and inform the farmer who is near to deliver. IoT-based livestock management helps farmer for good health of animals:

- Wearable sensors connected in IoT network allow farmers to observe blood pressure, heart rate, temperature, breathing rate, digestion system, and so on.
- Wearable sensor data saved on the cloud helps farmers to identify illness, other symptoms and feeding problems before they affect the animal's health.
- IoT network also helps farmers to keep track on the reproductive cycle of wildlife.
- Farmers can use IoT systems to monitor livestock generative cycles and the calving process to promote safe and successful outcomes.
- IoT sensors can also be used to keep track of an animal's locality.

4.2.2.4 Smart greenhouses

Basically, greenhouse is an urban farming method, which provides farmers the best farming condition using a proportionally controlled mechanism according to the crop's need for proper cultivation. But the use of traditional greenhousing involves manual intervention, resulting in a loss in production, energy, and cost of labor [16, 29].

To overcome such challenges, smart greenhouse monitoring and control system comes into existence. The increased use of technologies like IoT, ML, and AI is the main factor in the growth of greenhouse in the future years [16].

IoT-based greenhouse system helps to improve the quality of crops, fruits, and vegetables. This system controls environmental parameters with the help of automatic control. These systems mainly consist of the following stages mentioned in Table 4.4.

Table 4.4: Smart greenhouse automatic control stages.

Stage 1	Sensing	Uses sensors like temperature, light level, CO_2, humidity, water content, leaf wetness, pH, moisture levels, and nutrient concentration
Stage 2	Analyzing	Predictive analysis using different advanced machine learning algorithms, programmed control, and so on using various controllers
Stage 3	Controlling	Action based on analysis to control equipment like lighting systems cooling, heating system, harvesting equipment, irrigation controls, and door locks
Stage 4	Remote management	Remote monitoring as well as controlling is done using interfaces like web portal, smartphone app, and SMS alert.

4.2.3 Key advantages of using IoT in smart farming

As IoT is everywhere in the world because of its various benefits, and the following are advantages of using IoT in smart farming [17]:

1. **Easy access of real-time data**: Various important real-time data from various places of farms are essential for farmers to take correct decisions, which can be easily collected using sensors installed using IoT. Using IoT, it is possible to store this data in one place. IoT also allows farmers to share data, increase communication among farmers, and take advice from agriculture experts using mobile apps and IoT services by free or paid facilities.
2. **Reduced time and expenses:** The main advantages of IoT are its ability to monitor farming equipment and devices remotely. This saves time and cost of farmers instead of inspecting whole farm by either vehicle or walking. The ability of IoT to know precisely where to apply pesticides also reduces the expenses of farmers.

3. **Prevention of risk:** As through the IoT-based smart farming, farmers get up-to-date information about each process of plant; they can understand future risks and may take preventive action. This not only saves expenses of farmers but also gives nutritious and safe food. Also IoT can address food fraud and can be used to give logistics and qualitative traceability of food. There are several reports in food fraud that includes adulteration, counterfeit, and artificial enhancement.
4. **Competency:** The use of IoT is not only efficient to farmers but operational efficiency of IoT is also beneficial to government and nongovernmental organizations of the agricultural sector. Data collected from agriculture surveillance schemes via IoT can be used to prevent the spread of diseases, fire occurrences, and so on. The use of IoT in the food supply chain also helps to balance between supply and demand for food. IoT also enables real-time checking of farm assets and timely maintenance.
5. **Increased attentiveness:** IoT drives various applications through wireless network services in the agriculture sector. Therefore, agricultural market information, prices of agricultural products, and different services can be easily handled through mobile apps. And these immediate updates reached to the farmer make the farmer more competitive in agriculture sector. Farmers can reach consumers who are interested in high-quality and fresh food products.

4.3 Issues in implementing IoT

Investment in the agriculture sector is increasing rapidly in these years. Nevertheless, this growth of smart farming has some issues which are discussed here.

4.3.1 Social issues

1. **Cost:** Deployment of IoT is more expensive, and running of IoT includes purchase of hardware like IoT devices, base stations, and gateways. Also it includes the cost of exchanging data between IoT devices, energy, and maintenance costs. Cost of IoT is not moderate and hence it is not easy to middle-class farmers to purchase such systems easily.
2. **Connectivity in rural areas:** In various rural areas in India as well as in some other countries, high-range reliable Internet connectivity is unavailable. This is an issue to deploy IoT platforms in such areas, where actually there is more need for such system. Hence, till the speed of the network does not exceed in these areas smart farming implementation is difficult.

3. **Lack of knowledge:** Majority of farmers are from rural areas and are uneducated and, therefore, there is lack of sufficient knowledge of IoT and its application. Also farmers do not know detailed benefits of these technologies, and hence less adoption of these smart technologies.

4.3.2 Technological issues

1. **Data sharing in agriculture industry:** Recent advancements in new technology and AI create great combination of digital systems for development of agriculture and food industry, basically through data sharing. Data collection is done through various sources such as on-field sensors, remote monitoring of system, and agricultural drones, which are further used by ML algorithms. With larger amount of data collection, the challenge of data distribution comes into the picture. Access to farmer's field data and how it might be used against them is a serious reason of concern. Community sharing allows sharing of data to others and can be used to influence market conditions, which is an illegal case. Therefore, while implementing these technologies for agricultural growth they should focus on data transparency and control over the data usage [29].
2. **Data security and privacy:** Agricultural IoT industries need to think from security point of view for using new technology in right way. Use of latest farming techniques like precision farming puts this sector at higher risk of hacking and data theft due to significant absence of data protection. Hacktivist may use this data to protest. The transfer of data in between interconnected Internet of "smart things" must ensure security, authenticity, privacy, and confidentiality of various investors involved in this network [30].

   Data analysis practices are implemented by industries to make farming process more productive. But this sector is still predominant with traditional methods of farming which does not include any data backup or security concepts. For example, field monitoring drones/on-field sensors connect to farm devices and this device is linked to any general channel or Internet. Such channels fail to incorporate basic security features like session access, login details, and two-factor authentication.
3. **Device management capabilities:** Huge amount of real-time data collection is done through different on-field devices that provide better understanding of farming to farmers. With the development of technology, it becomes easier to information of specific territory with the community. This reason challenges farming systems to make device management, data storage and security, and deep analytics more capable.
4. **Interoperability:** Interoperability between number of IoT modules, devices, standards, architectures, and protocols is needed. Few policies related to interoperability include semantic, syntactic, technical, and organizational policy.

5. **Networks interruption:** Implementation of IoT devices uses various networks, for example, Zigbee, Wi-Fi creates problem of interference. The networks' interference finally results in loss of data and reduces reliability of IoT system.
6. **Technology selection:** With rapid growth in information technology, number of IoT technologies are being developed every day, and some of which are still in testing phase. Though the different technologies are available, selection of the right IoT technology becomes a difficult task since lot of investment is essential for deployment of new technologies.

4.4 Challenges of using IoT and ML

IoT has opened up new ways for agricultural sector growth through new productive methods of monitoring. ML along with IoT can do miracles and achieve new phase of exponential growth in agriculture field. Large amount of data generated from sensors can be used by ML algorithms to learn directly from database instead of depending on predetermined models. Though IoT and ML are beneficial for farming, there are certain challenges faced by these technologies in this sector as follows [1, 30]:
1. **Quality and durability of sensors:** This is considered as a challenge because high-quality and durable sensors cost little extra. Deployment of high-quality sensors in field is not affordable for farmers.
2. **Lack of awareness among farmers:** Farmers are less aware of agricultural machinery, which incorporates the latest higher technology. Insufficient knowledge of emergency technological trends in agriculture is a major challenge of using IoT and ML.
3. **Scalability:** This problem occurs when farms are very small in size and are fragmented thereby creating challenges for people who want to make profit or upscale.
4. **Accuracy of prediction:** ML prediction accuracy is affected by proper model representation, quality of data, and also by input and target variable dependency [16]. If quality of data collection, model representation, is not good then prediction process is not accurate.
5. **System design:** Implementation of IoT-enabled system and ML system for farming should be able to work robustly in outdoor conditions. Design of other IoT-based systems like agricultural drones and weather monitoring locations should be simple and functional and should have the required level of durability to work on the farm.
6. **Uninterrupted communication:** All coordinated devices will require uninterrupted communication infrastructure such as Internet and mobile broadband, coverage for which could be problematic in rural areas where virtually all farms are located. Connectivity failures may not give the desired outputs.

4.5 Conclusion

Compared to other sectors, agriculture industry has been experiencing a slower growth rate, but irrespective of other sectors' growth or business models, there will be a demand for food and agriculture products. Automated agricultural sector systems are expected to be more efficient and optimize the production process effectively. IoT technology helps in this regard, but the integration of IoT with predictive analysis of ML plays a promising role as the entire system becomes automated in true sense. Hence, the farming process is about to move from traditional ways to technology-enabled ways. Autonomous systems are not only capable of having command on interconnected devices but also have the ability to control production rate according to the market situation, maximize profit, and cut down cost in every possible way.

However, with the advancement in technology, plenty of players can participate. Every individual farmer may use various farming equipment with different characteristics and specifications; hence, interoperability needs a priority to be given. Also, local agricultural networks must be secured against intervention from other networks. In the near future, such interoperable systems will take over management, decision making, and monitoring tasks of farmers, which needs proper training for farmers to acclimate with new technology. Finally, the introduction of autonomous devices, vehicles, is likely to change the entire farming production and operation practices in upcoming days.

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5 Technological impacts and challenges of advanced technologies in agriculture

Abstract: In the present world, agriculture takes a vital part of the economy of many developing and developed nations through the production of food materials, generation of income, and industrial development. Thus, it has been considered as an essential and foremost sector worldwide. United Nation's Agriculture Organization (FAO) forecasts that the community of the world may reach up to 8 billion by 2025 and 9.6 billion by 2050. Primarily, this can be related to an increase in the production of food materials to around 70%, which must be achieved by 2050 worldwide. Globally, the cultivation of crops is being hindered by several biotic and abiotic factors, which significantly reduce the production and productivity of several economically important plants. Thus, the development of effective production and protection technologies is crucial to bring the maximum output. The recent advent of modern technologies, including the Internet of things (IoT) and machine learning (ML), has a high impact on agriculture. They are enabling agriculture to utilize data operated, directing to the more precise and profitable making of food materials through effective utilization of water and nutrient resources. The progress of ML and IoT has supported researchers to implement these methods in crop production (quality and quantity assessment), protection (identification of pest and disease), management (soil and water management), and livestock production and management which would enhance the production and productivity of crops and economic status of the farmers. This chapter highlights an overview of the modern technologies deployed to agriculture and proposes an abstract of the present and possible applications, and elaborates the challenges and suitable explanations and execution. Lastly, it presents some future directions for the IoT applied in the agriculture domain using ML and IoT.

Keywords: Internet of things, machine learning, agriculture, soil and water management

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https://doi.org/10.1515/9783110691276-005

5.1 Introduction

In India, agriculture and allied sector is the largest source of livelihood by providing employment, rural livelihood, and food security. The latest estimates show that 70% of rural households still depend primarily on agriculture, of which approximately 82% are small and marginal farmers [1]. Thus, the agricultural sector plays a crucial role in the economy, including trades and marketing of India. Crop cultivation is being hindered by several biotic (i.e., pests and diseases) and abiotic (extreme temperature, relative humidity, wind speed, light, etc.) factors, which significantly reduce the production and productivity of several economically important agricultural and horticultural crops. Besides, the poor agronomic practices, inappropriate selection of varieties, ineffective pest and disease management, inadequate supply of water through irrigation practices, and imbalanced nutrient and mineral supply also reduce the quality and quantity of crops. Thus, there is an urgent need to develop improved production and protection technology to enhance the production of crops. With this, the advent of modern technologies, including the Internet of things (IoT) and machine learning (ML), have a high impact on agriculture. They are enabled to generate the data sets (i.e., the influence of weather parameters, the number of inputs used or required, morphological and yield-attributing parameters of crops, and others) for enhancing the production and productivity of food materials through effective utilization of available resources.

IoT is mainly used to connect the network of things, which was embedded with sensor, software, and other technologies through the support of Internet without human intervention. This approach was developed and initially adopted by Kevin Ashton. In the beginning, this concept was broadly used in connecting the radio-frequency identification (RFID). Recently, the IoT is starting to impact in different fields and sectors ranging from production, medicine, communication, and agricultural sectors. Besides, IoT offering a broad range of capabilities including the communication infrastructure and variety of services including data acquisition from a local or remote area, intelligent information analysis, and decision-making through cloud-based approaches, user interfacing, and automation in agricultural sectors. Such abilities of IoT can revolutionize the agricultural sectors. Recently, the scientific community has focused more attention on the use of Internet-related technologies (i.e., IoT) in agriculture and allied sectors. In agricultural sectors, the IoT is also called as Internet of farming. In this chapter, we briefly discuss the technological impacts and challenges of IoT in agricultural sectors.

5.2 IoT uses in agriculture

- Monitoring of weather conditions – for example, IoT devices, allMETEO and Pycno
- Greenhouse automation – for example, Farm app and Growlink Green IQ
- Crop management – for example, Arable and Semies
- Cattle mating and management – for example, SCR and Cowlar
- Stem to stern farm management and practices – for example, Farmlogs and Cropio.

5.3 IoT applications in agriculture

5.3.1 Precision agriculture

Precision agriculture is often described as the precise application of farm inputs (fertilizers, pesticides, water, and seeds) and effective utilization of equipment (tillage equipment) for enhancing the sustainability, profitability, and environmental safety of the agricultural production system [2]. This precision system of agriculture has been widely used by the farmers for more than two decades to maximize profits, optimize inputs, minimize the cost of inputs, and minimize the impact of negative environments; however, there are several challenges including limited ability to integrate information from different sources, and poor understanding of agronomical practices leads to the excessive and moderate application of farm inputs resulted in the poor quality and quantity of food production. The current advance of the IoT has a high impact on the development of innovative and scalable approaches in the agricultural sector [3] and to overcome the abovementioned issues. More recently, IoT-based technologies with sensors are predominantly used in different sectors of agriculture [4] including monitoring of weather parameters, soil characteristics and fertility status measurement, pest and disease monitoring, irrigation monitoring process, and determining the optimum time for sowing and harvesting [5].

5.3.1.1 Soil properties and fertility measurement

Soil is considered as a foremost important factor for the cultivation of crops. A better understanding of soil properties, fertility status, and biotic and abiotic factors may help enhance the production and productivity of crops through nutrient planning and land-use pattern. Soil analysis through conventional approaches is the most common and frequent method for determining soil fertility and properties;

however, it takes more time. With this, the IoT-based electrochemical sensors approach with Wi-Fi module has been developed and utilized for assessing the status of nutrients in the soil (i.e., N, P and K) and also helpful for determining the crops suitable for that particular soil within a short period. Besides, several other IoT sensors have also been developed and used through the network of LoRaWAN, Zigbee, Sigfox, and Wi-Fi module for measuring soil pH, moisture, temperature, humidity, soil water potential, and soil oxygen levels [5–7].

5.3.1.2 Insect pests and crop disease monitoring and forecast

Cultivation of crops is continuously threatened by a diverse group of insect pests and plant pathogens, and these factors cause a significant amount of reductions in the growth, yield, and quality of crops. Monitoring of insect pests and disease is a crucial process by which the presence of insect pests and disease-causing organisms in a particular location can be assessed, and this information will be helpful for the development and deployment of effective pest and disease management strategies. Conventionally, traps including sticky traps, pheromone traps, and light traps are being used to monitor the activities of insect pests in the field, and image analysis system [8] is mainly used for monitoring the diseases. However, the abiotic factors including wind speed, temperature, and relative humidity are often obstructing the accurate monitoring of pests and diseases. The IoT technology (i.e., wireless sensor networks) based nodes have been developed and implemented in the agricultural area for monitoring physical parameters including insect pests. The nodes are involved in gathering the data and then forwarding the data to the sink nodes; the collected data were forwarded through the gateway, and then all the data were stored in centralized database stores. The suitable algorithms including correlation, linear regression (LR), and logistic regression are employed for assessing the monitoring of insect pests [9]. Studies have demonstrated the application of IoT in various pests and disease monitoring system [10, 11]

Forecasting is the process of making predictions of the future direction of infestation and infections caused by insect pests and disease-causing organisms. This information is crucial for deploying effective management strategies. A web-enabled forecast system has been developed based on the rationale of weather-based predictions of insect pests in the rice ecosystem [12]. In this study, the web application was designed on the three-tier architecture system, including client-side interface layer, application logic layer, and database layer (DBL). With this, the rules for pest prediction have been coded in C languages which are location and insect specific. DBL is worked on structured query language server 2008, where site- and time-specific weather-related data were stored.

5.3.1.3 Irrigation monitoring system

Irrigation is a practice in which an amount of water is supplied to plants at regular intervals. Sometimes, the cultivable land may receive an excess amount of water leading to water-logging, or might receive less amount of water, resulting in dry soil, which ultimately affects the growth and development of crops. Thus, the adequate and timely supply of water is crucial and the key to the success of crops. The monitoring of irrigation practices ensures the proper supply of water to the development of crops. With IoT, irrigation monitoring systems can help regularize the supply and control of irrigation water from an isolated area through sensors. Plant evapotranspiration is considered as an alternative parameter to determine crop irrigation. System-based evapotranspiration has developed and enabled water conservation on time-based irrigation [13]. Different types of IoT-based soil moisture sensors (i.e., ESP8266 NodeMCU Module and DHT11 Sensor) have been reported to be used in the agricultural system for monitoring the soil moisture, which cut down the excess or less amount of water through irrigation. Israel-based irrigation manufacture company (NETAFIM) has developed irrigation system sensors to monitor irrigation. Similarly, several sensors have been used to monitor and provide an adequate and timely supply of water.

5.3.1.4 Tracking and tracing

Locating the agriculture field and monitoring various agricultural activities are periodically monitoring through Global Positioning System (GPS) by using wireless communication networks [5]. Besides, the instruments including General Packet Radio Service and global system for mobile are also used to assess the soil structure and condition with the help of wireless sensor networks [14].

5.3.1.5 Internet-based system for farm maintenance

It is challenging to monitor and maintain the larger farm area with the help of a human being. With this, the IoT plays a significant role in monitoring (crop and soil characteristics, irrigation, weather parameters, farm facilities, machinery performance, and environment), documentation and traceability, forecasting, and controlling the farm activities through various sensors and model-based approaches. Farmers can observe data sets which were collected through wireless sensor network and the modules of global system for mobile via farm management system [15] for planning and preparation of farm activities in smart farming [16].

5.3.2 Greenhouse farming

Studies demonstrated that the implementation of IoT (i.e., WSN) in greenhouse significantly reduce the cost related to human resource operations and increase the production and productivity of crops [17–19]. Among the IoT approaches, wireless sensor networks are often used to monitor the climatic parameters, including temperature and relative humidity in the greenhouse conditions [5] presented in fig 5.1.

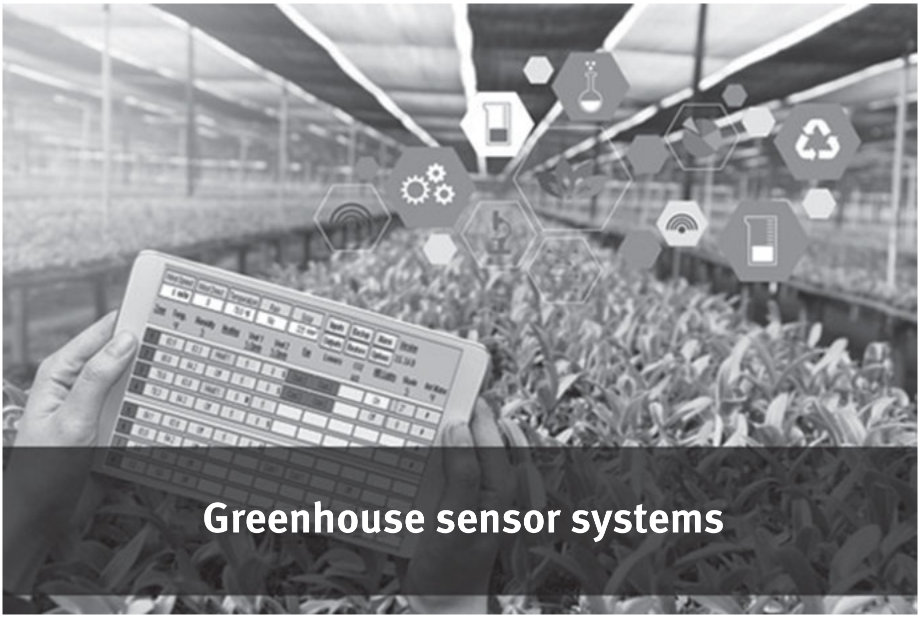

Figure 5.1: IoT-enabled greenhouse (Source: https://www.coe-iot.com/agritech/).

5.3.2.1 Water management

In the greenhouse condition, the amount of water required to grow crops depends on the area to be watered through the sprinkler, drip, and other methods. A periodical supply of an adequate amount of water is essential in greenhouse cultivation. IoT-based sensors and nodes are used for irrigation predominantly in water management in greenhouse condition through drip irrigation, overhead sprinklers, boom, and other methods [20].

5.3.2.2 Plant monitoring

Periodical monitoring of plant growth under greenhouse condition is essential to acquire the factors influencing or hindering the growth and development of crops.

IoT-based sensors and cameras are often used to monitor the state of plants regularly and generate data. The sensed data are stored in cloud-based IoT solutions and viewed periodically to monitor the plants in the greenhouse [21]; based on the sensed data, the cultivation practices are deployed.

5.3.2.3 Climate monitoring

Periodical monitoring of climatic factors including temperature, relative humidity, wind speed, air, and light in field or greenhouse condition is crucial for the growth and development of cultivated plants. The temperature requirements within the greenhouses vary from plant to plant. Internet-based sensors predominantly used for monitoring the temperature and relative humidity (DHT22), soil moisture (KG003), light-dependent resistor, and analog-to-digital converter are frequently used to monitor and maintain the optimum climatic factors under greenhouse conditions [20].

5.3.3 Livestock monitoring

Precision livestock helps to maintain an optimal environment or weather circumstance to increase the productivity of animals [22]. IoT-based livestock management solutions help to monitor livestock conditions [7]. Numerous IoT-based sensors are often used to monitor the performance of livestock including their health and nutritional status, temperature, and movement. With this, RFID is helpful to the farmers to track their location and monitor overall animals' activities. However, wireless sensors are predominantly used for monitoring the farm animals in more massive farms presented in fig 5.2.

5.3.3.1 Animal temperature monitoring

Body temperature is sensed to identify and prevent disease symptoms from monitoring the health of animals [23].

5.3.3.2 Heat stress monitoring

Stress caused by the temperature reduces the activity of cattle and is also reported to reduce the productivity of milk. With this, IoT-based sensors are widely used to monitor the stresses based on their behavior [5].

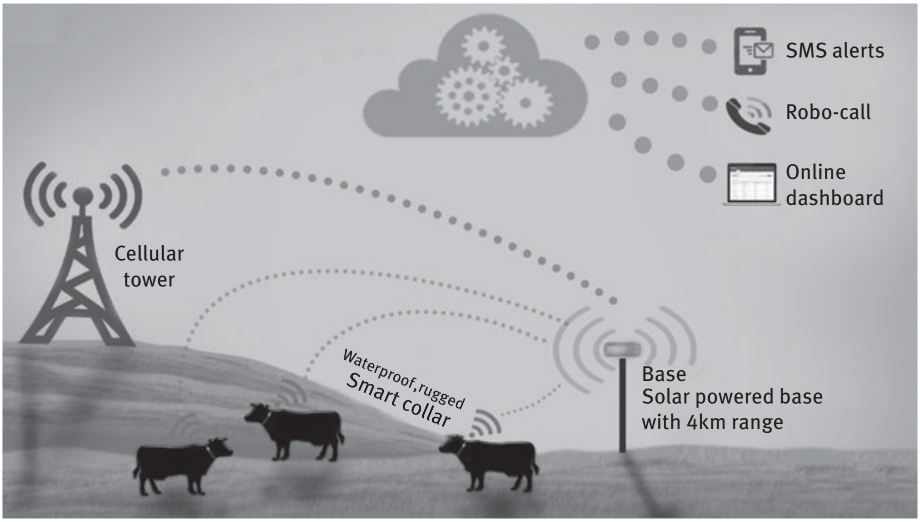

Figure 5.2: IoT-based livestock farming (source: [5]).

5.3.3.3 Physical gesture recognition, rumination, and heart rate

Using IoT devices and sensors, animal's gesture, behavior, rumination, and heart rate are often monitored [5].

5.3.3.4 GPS-based monitoring

Frequent monitoring of cattle in a larger area is crucial for protecting the farm animals from wild attack, theft process, and effects caused by unfavorable environmental factors. GPS-based monitoring system is frequently used to monitor the farm animals to prevent those issues. Wireless-based sensors, including Zigbee and LoWPAN, are widely used.

5.3.4 Smart phones as agricultural solutions

Many e-Farming apps are developed for agricultural information management (Farm Manager and Agriapp), agricultural calculations (blend calculator and fertilizer cost calculator), news and weather information (Accuweather), sprayer tank mixing (OnMRK), record keeping (AgDNA Prime), soil sampling (SOILApp), precision agriculture (Field Net), GPS applications (Field Navigator), and agricultural marketing (Crop Prices) [24].

5.3.5 Application of IoT-based sensors in agriculture

IoT-based sensors are predominantly used to monitor the abiotic factors including the maximum and minimum temperatures, relative humidity, soil moisture, the negative logarithm of hydrogen ions (pH) in soil and irrigation water, wind speed, and other factors in the agricultural field [5].

5.4 IoT services

5.4.1 FASAL

FASAL created its artificial intelligence (AI)-based weather forecast system, FasalμClimate, to reduce the costs of depending on the weather forecast from weather apps. The real-time in-field information, analyzed by the AI-based micro-climate forecasting algorithm, offers farmers with on-time details related to the farm operations in their specific farm fields [25]. Shanthi [26] reported that Fasal has mainly focused on innovative farmers growing various economically important horticulture crops, and also that farmers have a close association with the food processing industries. According to Ritesh [27], until now, the innovations in IoT in agricultural sectors are predicted to achieve the reduced cost of production and are readily available to the marginal farmers. To make the technology affordable to small and marginal farmers, FASAL adopted a business model that includes a nominal monthly subscription fee without any upfront charge or deposit. It is a pay-as-you-go model [25] architecture of FASAL in fig 5.3.

5.4.2 Opencube Labs at Bengaluru

IoT-based agricultural products that are farmer friendly are developed by Opencube Labs at Bengaluru and is open-source. The IoT devices assess crop health to get real-time data on soil health for smart irrigation scheduling and livestock management. These are built entirely in open hardware platforms, namely, Arduino and Raspberry Pi, along with ESP.

To know the exact quantity and the time of application of fertilizers, normalized density vegetation index (NDVI) is used. The sensor collects real-time data on soil moisture, nutrient content, and pH. The cloud system was used to analyze all the data sent by sensors and automated the irrigation scheduling. Further, it advises farmers about the optimum quantity of fertilizer and the time of application. Based on the parameters, the yield can be predicted, the appropriate seed variety can be

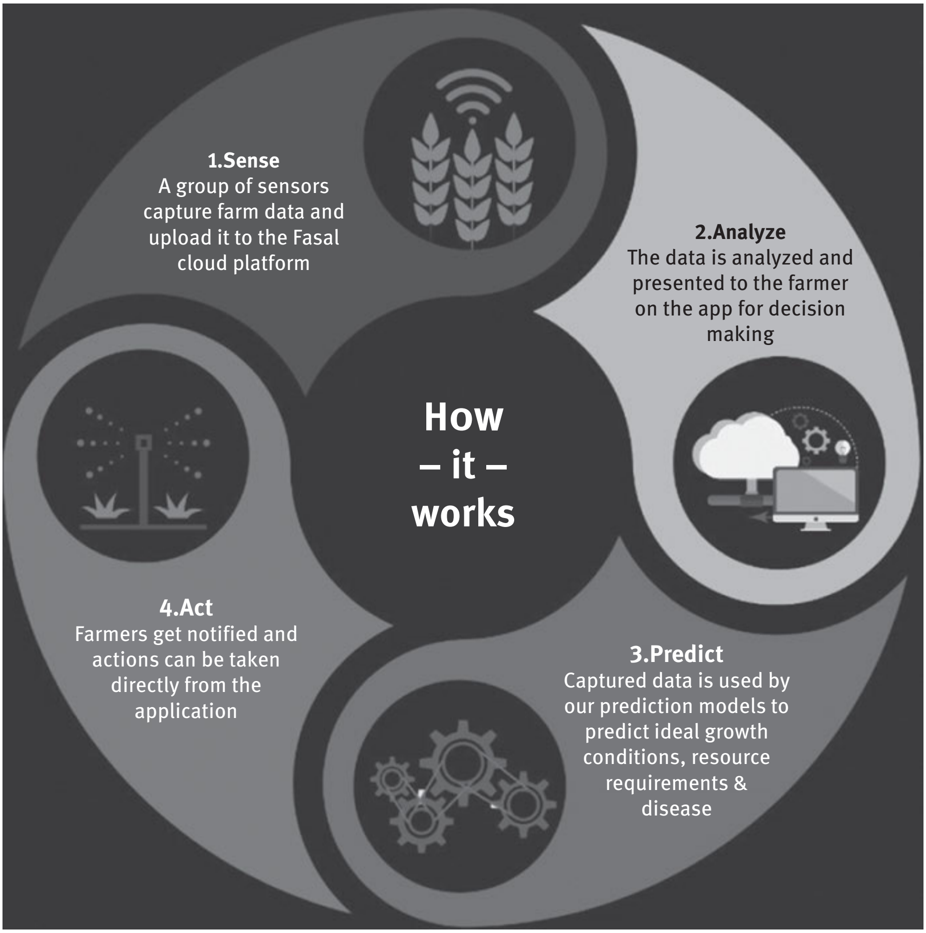

Figure 5.3: How FASAL works (source: https://fasal.co/).

selected, and protection measures can be implemented (https://iot.electronicsforu.com/expert-opinion/internet-of-things-in-agriculture-india/).

5.4.3 Next technologies

Pests and disease monitoring on large landholdings can be monitored effectively by combining IoT, AI-based image processing, weather forecasting, and satellite imagery on a single platform. It facilitates in developing the best predictive model (https://iot.electronicsforu.com/expert-opinion/internet-of-things-in-agriculture-india/).

5.4.4 Energy bots

The controlling of the water supply through a motor pump can be effected through a GSM-based three-phase IoT device. The sensors will collect the data on humidity, temperature, and moisture in the controller and microcontroller. Based on the data collected by the sensors, the farmer will be alerted through text messages or missed calls, or irrigation can be scheduled at an appropriate time (https://iot.electronicsforu.com/expert-opinion/internet-of-things-in-agriculture-india/).

5.4.5 Intello Labs

Supply chain management of agricultural produce can be digitized using AI. For this purpose, Intello Labs developed Intello track that grades produce based on color, size, and visual characteristics by capturing images through a mobile app. For segregation, they have developed a device, namely, Intello sort, again using the same criteria. For packing the products, another device called the Intello pack will be used to optimize packing efficiency. Intello deep is used to detect Brix, pH, total soluble solids (TSS), dry matter, moisture content, and pesticide residue. It is a hand-held near-infrared scanner (https://www.intellolabs.com/).

5.4.6 DigiAgri

The shortage of water for irrigation forced us to achieve "more crops per drop and acre." It will be more useful for smallholder farmers who are resource poor, and also significant in the future as free electricity is going to phase out soon. The "DigiAgri" products help to achieve this by collecting real-time data and making smart decisions (Table 5.1).

5.4.7 SankalpTaru

The mission of SankalpTaru is to create a healthy, green, and clean planet through tree plantation. The person who has contributed can select the tree, project area, and customize the plant. Notifications are sent to the contributor about the plant status, and there is a facility that the contributor can spot the tree sponsored through google map and receive periodic updates on its growth.

Table 5.1: DigiAgri products.

S. no.	Products	Scope
1	DigiAgri	Supply chain management for agribusiness can be done through digitization of farmer's activities
2	Farm App	Monitoring the farm activities at real-time can be done Advisory services on good agricultural practices through videos Geographic information can be used to plan cultivation of crops
3	FPO tracker	Real-time data can monitor the planning of crop cultivation, supply chain management, and inventory management
4	AgFin	Risk management can be effectively done by listing farm activities, estimating financial credit, and monitoring crop performance
5	AgChain	Supply chain management can effectively be done by mapping the produce ready for harvest, geotraceability, and resource planning at all levels
6	AgViewn	Providing information to the farmers on government schemes and weather aspects

Source: Author's compilation from http://digi-agri.com/products.php.

5.5 Benefits of IoT in agriculture

- Data collected by sensors used to track the performance
- Predict the production output and preparation of the plan for effective distribution
- Management of production cost and reduce the wastage
- Increase efficiency through automation
- Ensure the product quality and volumes

5.6 Challenges in IoT

- Lack of awareness among farmers
- The lack of knowledge as most farmers are illiterate
- Unaffordable due to high cost if quality and durable sensors used
- Small farm size and land fragmentation

5.7 Machine learning and their applications in agriculture

ML is a technology that aims to build an intelligent model that makes an accurate prediction without the intervention of human beings. The conventional ML approach is depicted in Figure 5.4. It constructs various algorithms to make effective decisions in the problem domain. The primary step is to select the data on the problem under investigation and to select the parameters for the examination. The model is trained by a sample set of data (termed as training data) to gain experience in the environment and make the model fit. Later, the model evaluated using a sample set of data (termed as test data). So this is the primary step involved in any ML model, that is, train–test–predict. Usually, the data set was divided into training (70%) and testing (30%). Testing data are kept separate and not used in the preparation.

The data set with many alternatives is collected and preprocessed using any normalization or standardization methods. The preprocessed data set was divided as train and test data set. The machine algorithms take the train data as input to train the model or to learn for the historical information. The trained model is evaluated with test data. The data visualization tools are used for visualizing the prediction or classification results. Algorithms involved in ML are supervised and unsupervised learning. In supervised learning, the model is trained with input data and mapped it into the known results, whereas in unsupervised learning, the model is trained, validated with input data, and finds all type of unknown patterns.

The most familiar learning models are clustering, regression, classification, and dimensionality reduction. ML utilizes a secondary data set (termed as validation data) for training the model further to avoid overfitting of the model by the trained data. If the model generates more error on data validation, it means that the model is overfitted with the prepared data, so the training is stopped. Now the data split can be done like 60%, 10%, and 30% of training, validation, and testing, respectively. ML is employed in almost all scientific applications such as health care, home automation, smart city, robotics, aquaculture, digital marketing, financial solutions, enterprises, climatology, food safety, and agriculture [28].

As agriculture forms the major economy for most of the countries, better assistance speeding up each stage of agricultural crop production is mandatory. ML and IoT serves this platform more effectively. IoT gadgets are used through wireless communication protocols to continuously monitor the crop, soil, water, and communicate their health to remote devices either by message or log data or buzzer to alert the farmers to take necessary actions. The data from these devices will make meaningful predictions and recommendations to the farmers through ML model or algorithms.

ML models are trained by the historical data of the agricultural field through which it gains experience and makes wise decisions for the data signals received from the IoT gadgets. The information received from these IoT gadgets must be secured and ensure confidentiality for accurate prediction results. Precision agriculture is a strategy adopted to integrate heterogeneous information (spatiotemporal data) for making precise and effective managerial decisions for global sustainable agricultural practices. Most of the parts of our country are adopting this strategy to improvise agrarian production in a brief span. Implementation of ML in smart agriculture has reshaped the plan, such as field-based crop suggestion, need-based fertilizer recommendation, water supply prediction, and harvest prediction, thereby controlling the water usage by supporting farmers for better yield in a smart way [29].

Digital agriculture (a term coined by use of precision agriculture and remote sensing) evolved to increase the productivity of crops with a minimized impact on environmental factors. Digital agriculture uses the data (crop, soil, and weather) sensed from the IoT devices to make effective decisions on nutrient-demand-based fertilizer recommendation, adequate supply of water through proper irrigation, soil nourishment, weed management, insect pests, and disease management [30]. Digital agriculture focuses on the best-of-breed optimization algorithms for crop production and its protection during growth. Multicropping is a technique adopted in digital agriculture or smart farming, which allows the cultivation of more than one crop in a single cultivable land [31].

Digital agriculture has to take more precautionary steps while feeding these different crops with competitive weeds and fertilizers as the mixed plant has a different nutritional requirement and water supply. So, it takes into account inter- and intravariability among the crops before feeding the fertilizers. It adopts techniques like in-row treatment to spray fertilizer for each plant separately, sensor-equipped drones to track the weed, automated sensing of fertilizer details from the barcode label for a correct proportionate mix of fertilizers, drift reduction techniques and integration of these applications with global positioning system, and comprehensive information system for periodic relay to the agriculturalists [32].

The ML approaches with different models/algorithms are actively deployed in different steps of crop cultivation including land suitability analysis, appropriate crop selection, crop production, crop protection, nutrient supply, water supply, crop health monitoring, yield prediction management, and postharvest management. The application of ML in different stages of agricultural crop production is depicted in Figure. 5.5.

5.7.1 ML in land suitability analysis

Land suitability analysis has been done for any barren land before permitting any residential plots to be constructed on that land. By ensuring better land use analysis, most of the agricultural land is not converted into residential buildings or industrial areas. Cultivating a crop without suitability analysis may lead to an enormous waste of time, more fertilizer supply, abnormal water requirements. Therefore, land suitability analysis for the cultivation of crops is an essential factor in ensuring sustainable agriculture yielding better production presented in fig 5.4.

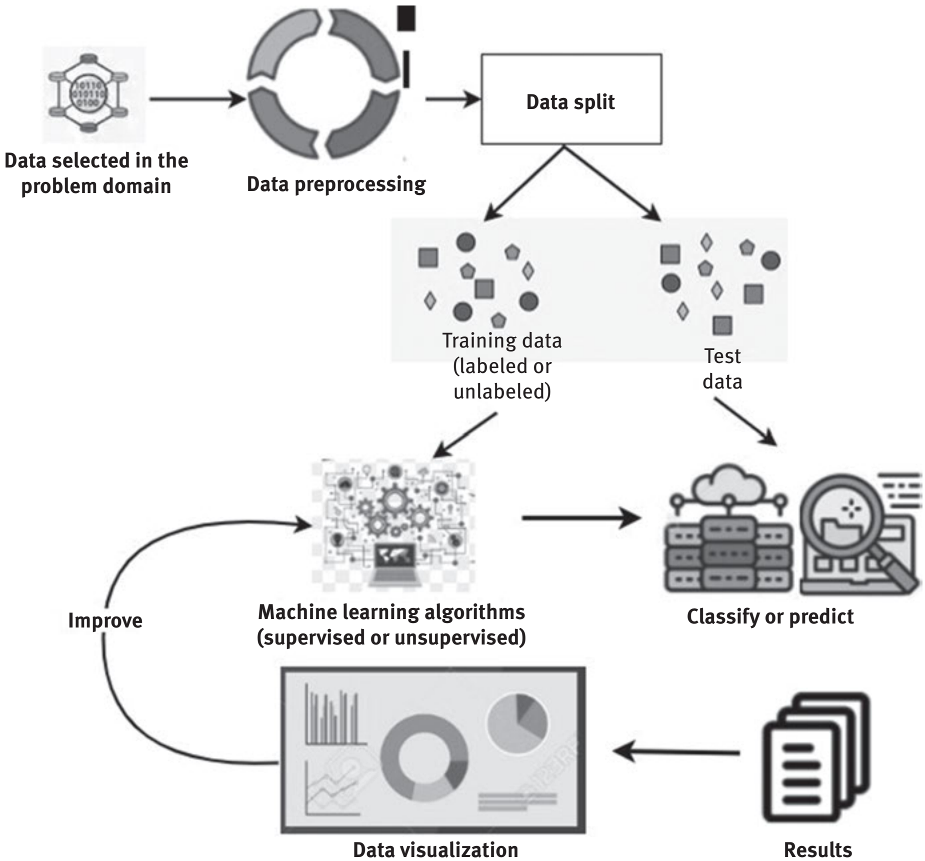

Figure 5.4: A machine learning approach.

Geographic information system (GIS) provides more significant support in aiding the suitability analysis of the land. Multiple factors are considered for analyzing the land suitability attained from advanced GIS systems [33]. The factors including soil properties, the topography of the land, water and nutrient availability of soils, and socioeconomic factors are considered as significant factors for land suitability analysis [33, 34].

Mokkaram et al. have implemented an ensemble classifier method, namely RotBoost, an integration of Rotation Forest, and AdaBoost algorithms for soil suitability exploration [35]. Benjamin et al. have assessed the suitability of land for cultivation of a different variety of rice crops in rural Thailand using species presence prediction method and demonstrated that the MaxEnt model outperforms and provides better crop suitability on particular land.

Senagi et al. have applied parallel random forest (PRF), support vector machine (SVM), LR, k-NN (k-nearest neighbor), linear discriminant analysis, and Gaussian–Naïve Bayesian to ensure the land suitability for the cultivation of sorghum [36]. PRF provides better accuracy than others when evaluated using 10 cross-fold validations. One of the most important attributes that contribute to suitability analysis is soil quality. The moisture content in the soil helps to determine the suitability of growing a particular crop in a land. Typically, the dryness or wetness level of the Earth can be determined by considering the same at other locations, which has similar soil type and hydroclimate [37].

The accuracy of land suitability analysis varies from soil to soil; a study demonstrated that the land suitability analysis was more accurate in the soil with more drainage (sandy soil) than poorly drained soils [38]. Soil fertility levels should be periodically monitored and maintained at appropriate levels for the continuous nourishment of crop production in agricultural land [39]. All these approaches use the data obtained through remote sensing and IoT devices. A better understanding of the land suitability analysis of the agricultural land will help select the suitable crops and fertilizer recommendations to make it better nourished for growing suitable crops.

5.7.2 Machine Learning in crop production

Crop production includes the selection of crops, preparation of soil based on suitability analysis, sowing seeds, application of manures and fertilizers, water management through proper irrigation mechanisms, harvesting, and postharvesting process. ML helps the agriculturalists in making better decisions in crop quality determination, yield prediction, plant species determination, crop disease prediction, and harvesting techniques.

The data obtained through IoT sensors in the agricultural field is considered as input data for ML. ML algorithms with the field-collected data train the model using history and can make predictions at any stage of production to determine the different features required to predict the yield. It will help to improve the quality and quantity of the next crop. Consequently, the crop production price will show a dramatic improvement in the upcoming yield. Image processing techniques integrated with ML suggested for plant species identification for the given crop image [40] presented in fig 5.5.

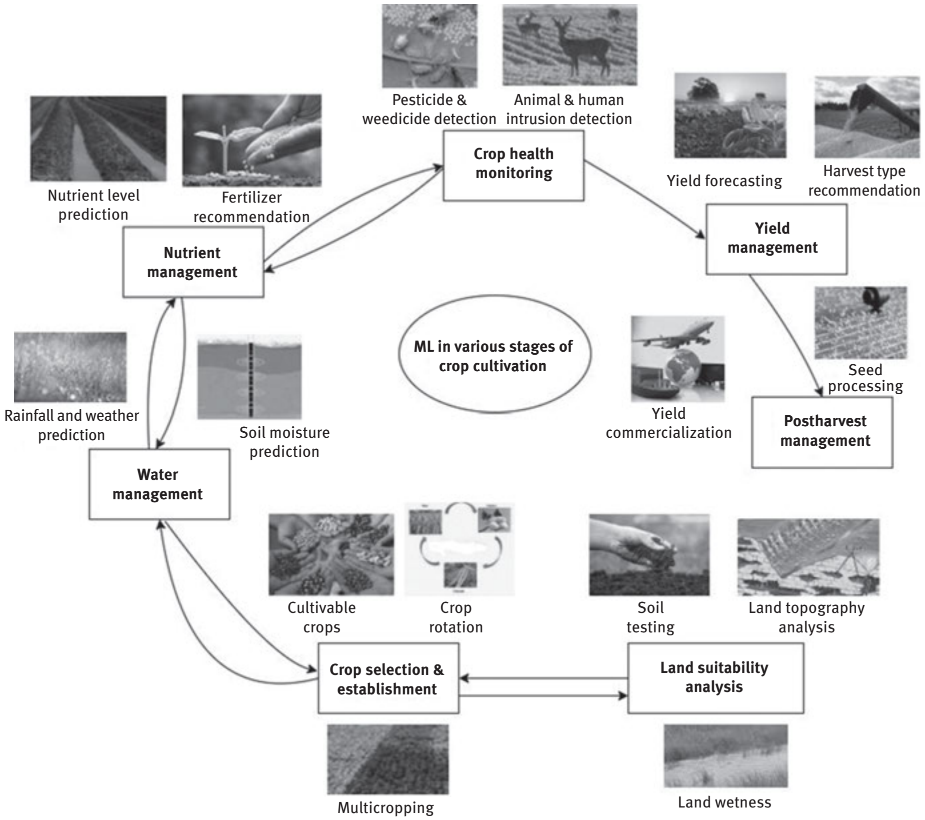

Figure 5.5: Machine learning in agricultural crop cultivation.

Land-specific yield prediction may be helpful for enhancing the yield through various cultivation practices. With this, different topological algorithms including artificial neural network (ANN), backpropagation, and multilayered perception through the implementation of a neural network are often used for land-specific yield prediction [41, 42]. Besides, the support vector regression (SVR) module is also utilized for crop yield estimation [43].

Though various decision support systems for better agricultural decisions, the agriculturalist has to deal with enormous heterogeneous data for making wise decisions, so ML plays a vital role. Chlingaryan et al. [44] have analyzed the various ML approaches and signal processing methods utilized for crop yield identification and revealed that backpropagation neural network provides the best precise crop yield identification (by considering the importance of vegetative indices), convolutional neural network (CNN) with Gaussian process is best for feature extraction, and best multiclass crop estimation by M5-Prime RT.

A comparative analysis of ML algorithms, such as M5-Prime, k-NN, SVR, ANN, and multilinear regression model, on the prediction of crop yield demonstrated that M5-Prime outperforms followed by k-NN, SVR, and ANN. It was evaluated based on the accuracy metrics (normalized mean absolute error, root relative squared error, root mean square error, and correlation factor) [45]. Corn yield prediction was predicted by backpropagation neural network whose efficiency tested on green vegetation index, normalized difference vegetation index, perpendicular vegetation index, and soil-adjusted vegetation index.

Periodic drought assessment is essential for crop maintenance and water management. ML techniques involving random forest, cubist, boosted regression trees, SVR, coupled wavelet ANNs, and ANN are often used for drought assessment [46, 47].

5.7.3 Machine learning in weed management

The unwanted or undesirable plant in a cultivable land is called weeds, and they cause a significant amount of yield loss through the competition of nutrients. Thus, the accurate identification of weed species and their population is considered as crucial for the management of weeds. Different ML models/algorithms including k-means clustering, SVMs, and neural networks are being frequently employed in precision agriculture for the management of weeds [48].

Milk thistle, *Silybum marianum*, a noxious weed, causes significant amount of crop and yield loss in several economically important crops. The accurate identification and management of this weed is crucial. The ML approach of counterpropagation ANN, XY-fusion network, and supervised Kohonen network with multispectral image has been demonstrated for accurate identification of marianum from other crops. Similarly, several weeds have been identified through ML approaches.

5.7.4 Machine learning in pest detection

The images acquired through the optical sensors attached to Unmanned Aerial Vehicle (UAV) used in detecting the pests. CNN provides better results in this classification of pests from images [49]. Corrales et al. have suggested a list of supervised ML algorithms used for crop protection in terms of diseases and pests. They are SVM, k-NN, ANN, decision trees, and Bayesian network. Decision trees, SVN, and ANN are best for prediction and classification of pests, whereas Bayesian networks and k-NN are excellent in training [50]. These pests have a devastating effect on the crop storage and precautionary measures taken by identifying the categories of pests and their nature of the occurrence. Crop image analysis is used to categorize the type of pests using computer vision. Cheng et al. have implemented a deep residual learning model for classifying the pest image and it outperforms the backpropagation neural network and SVM in the precision of the pest image recognition [51]. Also, it provides better performance than deep CNN (AlexNet). CNN-based approaches have been employed insect pests identification in paddy tomato [52], and banana [53]. Therefore, integration image processing or computer vision and ML CNN algorithms provide the best identification tools for plant pests and defect.

Animal intrusion detection is mainly used to save the agricultural crop. These intrusions were identified and detected to avoid loss of crop production. IoT sensors provide periodic alerts on the detection of an animal object like rats, cow, sheep, elephant, and other wild animals. It can be detected effectively and prevented through wireless sensors alerts to farmers mobile and ML algorithms based methods used for object identification [54–57]. Also, ML algorithms are used to predict the animal or human object entry prior to training the model with past data from IoT sensors.

5.7.5 Machine learning in livestock management

Livestock management is essential for animal husbandry and the well-being of rural people as this frames a significant economic factor for rural beings and sustainable agricultural practices. Livestock species are used for varied purposes such as employment for the community, food supply, nourishing the family nutrition, significant income to few families, soil enrichment, and believed ritual events [58]. Livestock management includes vaccination for cattle species, health monitoring of livestock, managing livestock during drought, feed schedule, grazing, milk quality management, ketosis for dairy animals, ear tagging, production, and castration. In livestock management, different model/algorithms are being used for classification, identification, and tracking of animal behaviors. The EL/bagging with decision trees of model/algorithm is mainly used for classification of cattle behavior-based features like grazing, walking, sleeping, and ruminating [59] for recognition and grading of chewing shapes in calves using decision tree/C4.5 based on chewing signals while dieting ryegrass, supplements, hay, rumination and during sleep, behavioral changes monitoring and tracking of pigs, and behavioral annotation mainly depends on Gaussian mixture model based on 3D motion information [60], ANN for determination of rumen fermentation [61], CNN for face recognition of pigs [62], estimation of beef's carcass weight using SVR models, SVM models for early evaluation of egg production in hen and bovine weight estimation in cattle [63–65].

5.8 Conclusion

IoT and ML will bring revolution in the agriculture field with continuous improvement in technology. The cost of the IoT products should be affordable for the small and marginal farmers as these products occupy a significant portion of the farming community. The corporate sector entering the agricultural industry is a good sign for the IoT companies as there will be a massive demand in the future. The vagaries of nature due to climate change effects, coupled with the labor shortage for agricultural operations, will favor the usage of IoT devices in agriculture positively.

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Part II: Applications of Internet of things in agriculture

Aarti and Amit Kumar

6 IoT-based platform for smart farming – Kaa

Abstract: Agriculture is considered to be the backbone of the Indian economy, which has made some fantastic progress due to substantial equipment like tractors. Well, it is very reasonable to feel that any development in agribusiness, which sets aside money and time, must be something to be thankful. Farming has seen different innovative improvements in the most recent decades as well as now becoming more industrialized and technology driven. But the truth of the matter is that the most of our farmers need legitimate information about the advantages of air quality, appropriate soil moisture and its quality, and water system, in the development of crops which makes it considerably progressively sporadic. A large portion of farming and agrarian activities depend on forecasts, which on occasion fall flat. In this way, by utilizing different smart agribusiness devices, ranchers have gained improved control over crop production and raising domesticated animals, which makes it more productive and predictable. With the increasing acceptance of the Internet of things (IoT), IoT gadgets, for example, vehicles, PDAs, smart sensors, and electronic appliances linked to a wireless network, are used in various fields.

Sensors gather a huge measure of ecological and field performance data like time-series data from sensors, ranging to spatial information from cameras, to human perceptions recorded and collected through smartphone applications and software. It can transfer the information to the cloud or directly exchange data with other linked gadgets. It can be used in farming to improve the quality of agriculture. Then, an analysis of such data can be done to find out irrelevant data and also calculate customized field proposals for a particular farm. As the information is stockpiling, sensors, web, and analytics have become less expensive, quicker, better, and progressively coordinated together. Now, users have the option to rely on an investigation to make better choices. Numerous parts of our lives, including home automation, fitness and health, automotive and logistics, industrial IoT, and smart urban communities, will significantly be affected by IoT gadgets. As IoT has encouraged the conviction, a smart network sensor, robots, drones, camera, and other associated gadgets will automate decision-making to agriculture and bring an exceptional level of control which would improve many facets of the farming practice. Nowadays, the advancement of deep learning, IoT, and machine learning has accumulated the full consideration of specialists to apply these methods in fields like agriculture. Two factors will severely affect the cultivation of crops. To commence with, environmental change is expanding the severity of droughts and frequency, permitting destructive

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https://doi.org/10.1515/9783110691276-006

insects to flourish. Second, the baby boomer breed of farmer's retirement and a deficient number of substitution laborers will leave farms in need of help. Sensors introduced near the farm are used to gather information. Drones are also accumulating information from the fields; in this way, farmers can lessen wastage in water and compost by distinguishing the best time to produce, sprinkle, or harvest.

The rising concept that alludes to overseeing ranch using (using advancements like IoTs, automatons, and robotics to enhance the amount and trait of items) modern information and communication technologies can enhance the trait and number of items while improving the social work that is known as smart farming. No doubt, the IoT is the main thrust of smart cultivation which connects sensors and smart machines incorporated on a ranch to make farming method data-enabled and data-driven. Large-scale farming activities are not the only objective of IoT-based smart farming. The value can also be increased to the latest trends in agriculture like family farming, organic farming, which includes rearing specific dairy cattle as well as developing particular societies, conservation of specific or good quality varieties and improve exceptionally straightforward farming to society, consumers, and market cognizance.

The latest advancement in innovation significantly affects agriculture, which can lead to high revenue. This chapter focuses on the work done by the IoT-based platform, and also discusses Kaa, an IoT-based platform for smart farming that makes farmers reply instantly toward developing issues and modifications in encompassing conditions as well as examine their benefits.

Keywords: smart farming, Kaa, IoT platform

6.1 Introduction

Smart farming is an idea of agriculture management by utilizing current information and communication technologies (ICT) to enhance the amount and quality of items [1]. Nowadays, an agronomist has accessibility to Global Positioning System (GPS), data management, soil examining innovations, and Internet of things (IoTs). By correctly estimating varieties inside the field and adjusting the procedure according to that, farmers can extraordinarily build the adequacy of pesticides and composts, and utilize it more precisely. With the utilization of smart farming methods, they can, more likely, screen the requirements of each animal and change their nutrition correspondingly, along these lines curing disease and improving group well-being [2]. It is a most recent and feasible answer to deliver the best and futuristic technology on a smart farm, supporting a community of small farmers and protecting water. India is a developing nation and has a tremendous commitment to the sustainable power source sector with as much as 107.22 billion units in 2019 [3]. This activity has empowered to fix a benchmark for sustainable measures and provide a future-proofed green planet [4]. Smart farming is an administration idea concentrated on giving the agricultural business with the framework [5]. Instead of fighting with problems like extraordinary climatic situations, the rise in environmental change, and cultivation's essential result, the concern for more nourishment should happen [6]. For this, agribusiness needs to go toward the latest innovation. It is a capital intensive and one of the applications of modern ICT in agriculture [7].

Improving ranch efficiency is fundamental for expanding ranch gainfulness and fulfilling the fast-developing need for nourishment that is fueled by fast population development over the world [8]. Yield suggestion is as of now dependent on information gathered in field-based rural investigations that catch filed performance under some situations like ecological conditions and soil quality [9]. But crop execution information assortment is as of now moderate, as such yields considered are regularly embraced in remote and disseminated areas, and such information is gathered physically [10].

Rising IoT innovations, for example, IoT gadgets like cameras, remote sensor systems, and network associated with climatic stations, smartphones are used to group tremendous measure of environmental [11] and harvest execution data, to human perceptions accumulated and recorded through portable PDA applications. Such information would then be broken down to filter from worthless data and calculate customized field suggestions for a specific farm [12]. The use of modern ICT into agriculture is known as the Third Green Revolution [13]. Following the plant reproduction and genetic qualities, it is assumed to control over the horticultural world dependent on the consolidated use of ICT setup, for example, Big Data, IoT, accurate hardware, GPS, sensors and actuators [14], unmanned aerial vehicles like drones, and robotics [1].

From the rancher's perspective, smart farming should furnish the ranch by including an incentive as better dynamic or progressively productive exploitation activities and the management [13]. AgriTech or smart cultivating is the advanced act of outfitting farms and farmers with innovation [15].

Among the innovations that are accessible to farmers are:
– Sensing innovations which include soil filtering, light, water, stickiness, and temperature management
– Software applications – particular programming arrangements that focus on explicit farm types
– Communication advances, for example, cellular communication
– Positioning advancement which includes GPS
– Hardware and programming frameworks that empower IoT-based arrangements, mechanical autonomy, and robotization
– Data investigation that underlies the dynamic and forecast process.

Furnished with every conceivable tool, agronomist can screen the crop conditions without heading off to the field and settle on vital choices for the entire farms [16]. The main thrust [17] is the IoT – the idea of associated smart machines and sensors incorporated on the ranch to make cultivation process data-driven and information empowered Figure 6.1. The IoT-based smart cultivation is exceptionally capable as distinguished to the traditional cultivation techniques [18]. Greenhouse's real-time monitor, water savings, crop diseases, and other IoT features are some of the tools that will improve agriculture and farming of the future. The introduction of IoT technologies in agriculture is like a game changer in the world. The efforts related to IoT help the farmers to get inside details of crop production and can also improve the quality and safety of crop [19].

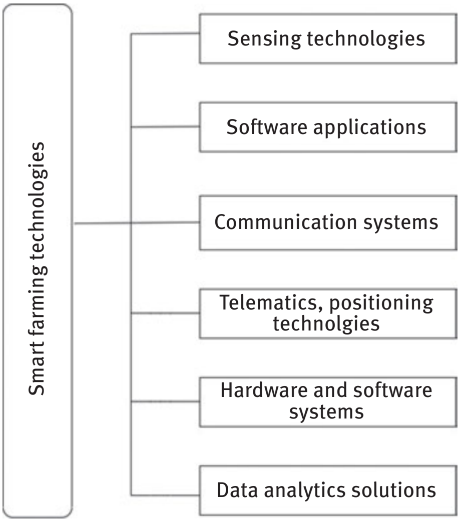

Figure 6.1: Technologies involved in smart farming.

A lot of literature is available on IoT-based smart farming from various sources, such as blogs, forum posts, conference proceedings, and journal articles. Prathibha et al. have discussed the use of developing technology and working on IoT-based monitoring system in smart agriculture using automation [20]. Rao et al.'s primary focus is to give necessary water to the ranch at the right time [21]. Manasa et al. have discussed the sensor technology and wireless network in combination with IoT based on the agricultural system [22]. This chapter focuses on the IoT-based platform – Kaa – with their advantages and various applications of smart farming.

6.2 Need for smart farming

Information and capital are basic for any development. New cultivating advancements require an ever-increasing number of expert aptitudes. Today, a farmer is not just an individual with energy for horticulture, the person is likewise a legitimate master to discover his/her way through a developing maze of guidelines. Low-maintenance information investigator, financial analyst, and accountant from selling agrarian produce require accounting abilities and inside information on showcase chains and value unpredictability. Fortunately, there is a broad range of alternatives that are accessible. From utilizing low capital speculation, advanced mobile phone applications track domesticated animals to a capital-escalated robotized combination. On a fundamental level, actualizing smart farming advancement can be effectively upscaled [2].

6.3 Smart farming cycle

The core of IoT [23] is the information, and more information is drawn from things and is transferred over the Internet. To improve the cultivating process, IoT gadgets introduced on a field should gather and process the information in a monotonous cycle which empowers ranchers to respond rapidly to developing issues and improvements in encompassing conditions [1].

It follows a cycle like this.

1. Perception
   Sensors record information observed from the fields, soil, animals, or environment.
2. Diagnostics
   The sensor takes care of cloud-facilitated IoT stage with predefined choice standards and models which is also called a business rationale that learns the state of the analyzed object and recognizes insufficiencies or requirements.
3. Choices
   When issues are uncovered, the client, as well as AI, has driven parts of the IoT stage to decide if explicit area treatment is vital and true.
4. Activity
   After end-client assessment and activity, the cycle rehashes from the earliest starting point.

6.4 IoT-based platform – Kaa

IoT has opened up amazingly profitable methods for farmers and growers to cultivate the soil and raise domesticated carnal using modest [24] and a plethora of perceptive data. Prevailing on gainful development of the IoT in agribusiness, smart developing uses are making progress with the assurance to convey 24/7 detectable quality into the soil and yield prosperity, equipment utilized, vitality utilization level, and creature behavior [25]. Kaa permits to make brilliant applications for the

IoT as it is a multireason middleware stage [26]. It gives an open, feature-enriched toolbox for the IoT item creation procedure and significantly diminishes the related costs, dangers, and time to advertise. It offers a lot of IoT tools that can be effortlessly connected and actualized in a more significant part of the IoT use cases.

Kaa is an important middleware [27] advancement which allows walking safely into the horticulture IoT farm. By integrating connected gadgets, various sensors [24], and cultivation facilities, it smoothes out the improvement of the smart farming system to the most extreme conceivable degree. It is superbly feasible for smart farming items such as smart meter gadgets and domesticated animals trackers. Kaa is as a feature-rich open-source stage that gives full rights to its components for any essential adjustments, expansions, or combinations. Kaa, as of now, gives a lot of available to-utilize parts for a speedy beginning with the smart cultivation application. After considering all the things, farming is all about association with nature.

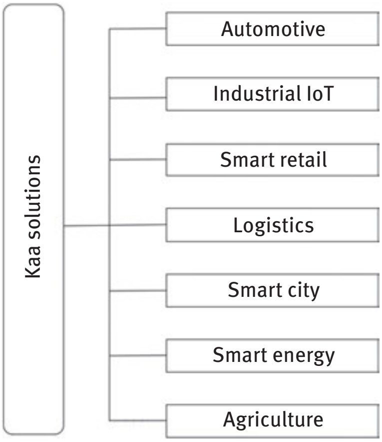

Figure 6.2: Kaa solutions for smart farming.

6.4.1 Possibilities with Kaa

- Sensor-based field and mapping of asset
- Observation of remote gear
- Observation of remote harvest
- Predictive examination for yields and animals
- Monitoring and forecasting of climate
- Following the livestock
- Stats on taking care of domesticated animals and their produce
- Smart coordination and warehousing

6.4.2 Advantages of Kaa

- Kaa gives various basic points of interest in fast IoT improvement and arrangement.
- It depends on adaptable microservice engineering and open conventions empower and endeavor grade adaptability, security, and spot a solid accentuation on the designer's opportunity concerning their decision of innovation, kind of organization, and outsider incorporations [28].

6.4.3 Customized microservice architecture

Each element of the Kaa stage, for example, informing or representation, is an assortment of microservices that play out their particular capacities. Microservices streamline customization and guarantee compelling partition of worries between various parts of the stage.

The Kaa microservices communicate through open APIs and can be incorporated with outsider frameworks and revised according to necessities. These microservices can even skip that is not required or supplant any of them with their segments.

6.4.4 Freedom of technology

Following the best business methods, Kaa runs its microservices in Docker containers. It implies that DevOps tools can be applied while executing Kaa-based arrangements in any condition.

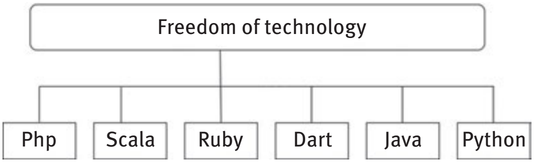

Figure 6.3: Freedom of technology.

Also, it utilizes very much characterized interfaces dependent on REST and NATS, which makes it innovation rationalist and permits to create and convey applications written in any programming language for all intents and purposes.

6.4.5 Freedom of deployment

Kaa services can freely be deployed from anywhere. It can be done at own data center premise or can also be hosted on some public cloud framework. The stage is also ideal for hybrid arrangements, for instance, when an organization runs Kaa in its data center and scales it into the cloud at whatever point the presentation request increments.

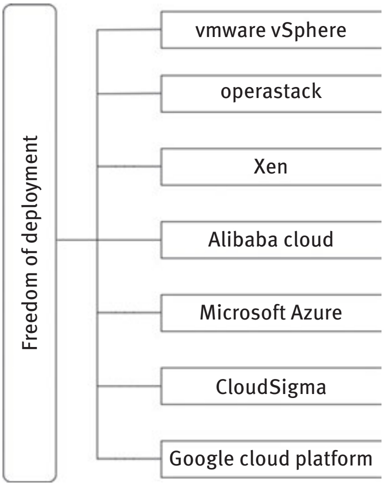

Figure 6.4: Freedom of deployment.

Private cloud and on-premise deployment alternatives give the full command over the framework, which is regularly a necessity in tough security areas.

6.4.6 Multiapplication

Kaa application characterizes a different kind of gadget that has an interesting arrangement of capacities and abilities like a vehicle, fitness tracker, or a telecom retransmitter. Each Kaa endpoint is credited to one application that helps to sort out the gadget biological system, disconnect the functionality of gadget usefulness, and oversee information streams in the stage. A Kaa solution group can provide various Kaa applications, taking into account cross-application association.

6.5 Working of IoT in agriculture

It is not a hidden fact but a mystery that IoT has changed the whole scenario. Indeed, it has presented advancement in different ventures that helped with expanding the adequacy and reducing the expenses of business activities in various angles [29]. The area of farming fits this pattern completely. Being beforehand reliant on HR and hardware totally, it has likewise begun applying innovative arrangements and modernizing its central activities. Thus, it is conceivable to examine farming IoT as the entire circle. To address this undertaking, we find the principle headings where IoT applications in agribusiness figured out how to have a huge effect.

6.6 Technological trends in agriculture

Smart urban communities are touted to be the spots that will oblige the requests of the developing populace on the planet. Urban cultivation can fulfill the expanding nourishment needs alone, and accordingly, many smart urban areas have their dominant part of a spotlight on the equivalent [15]. These days, rather than moving the agribusiness legacy of the wide open to urban space, it is unquestionably progressively productive to update the wide-open cultivation. Truly, current and approaching advances, including IoT-empowered sensors, drones, and self-governing robots, are finding their applications in countryside smart farming [30]. From seed to the water system to field's well-being and harvesting, mechanical advancements can possibly upset customary cultivation. Farms are one of the most significant biological systems for the endurance of the open country [15].

As per BI Intelligence forecasts, the amount of IoT gadget foundations in agribusiness will arrive at 75 million in 2020. The arrangement of smart farming is growing bit by bit.

6.7 Applications of IoT in agriculture

IoT can increase the value in all zones of farming, from the growth of fields to forestry.

6.7.1 Precision farming

This methodology is based on IoT that causes cultivation to be composed and precise. In general words, plants and dairy cattle surely get the treatment they require, decided with incredible precision [31]. The greatest distinction from the old-style method is that it permits choices made based on per square meter or even per plant/

creature instead of only for a field. By estimating varieties inside a field, ranchers can help the viability of pesticides and composts to utilize it specifically [1].

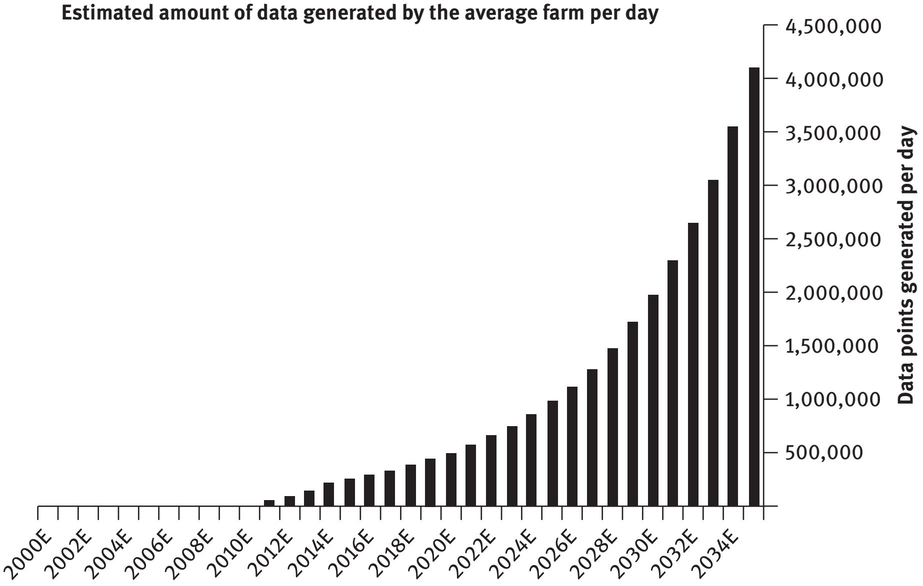

Figure 6.5: BI Intelligence report [16].

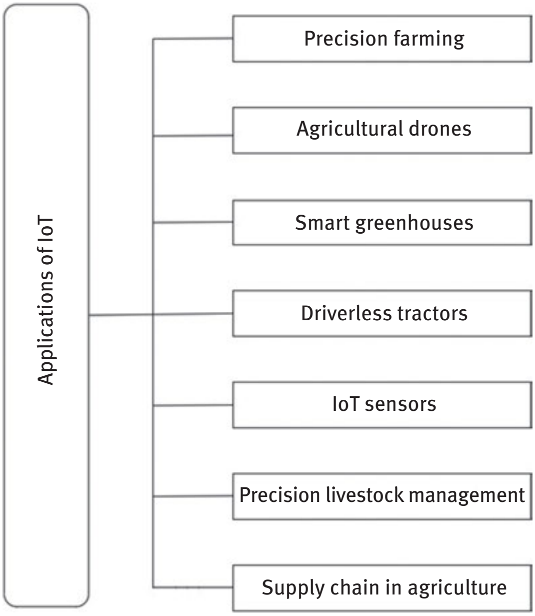

Figure 6.6: Applications of IoT.

6.7.2 Agricultural drones

The 1,000-year-old method of driving out fowls through scarecrow currently appears to be not any more viable when these smart winged creatures are nearby. Drones are used to drive winged creatures off from rural fields. One of the most helpful uses of drones found observation and examination of fields progressively [17]. The benefits are 10 times when a fleet of drones is utilized instead of a group of laborers going through hours on a vehicle to monitor the crop conditions outwardly.

Nowadays, helicopters and small airplanes are utilized over the fields to catch aerial pictures. But drones outfitted with cameras can be better at catching images at a small amount of the expense. Drones outfitted with advanced camera frameworks are accessible to catch photographic imaging extending from standard to infrared to bright image. Cameras can even record video. Furthermore, the picture resolution utilized by the drones is continually improving, which can assist farmers in getting exact information about the fields. No doubt, exact and detailed information can upgrade a farmer's ability to screen crop well-being, evaluate soil quality and plan seeding areas. Drones can improve anticipating seed planting patterns, water framework, and land mapping in both two and three dimensions through regular field study. This strategy brings about the general advancement of assets and also the land. Farming is the significant vertical, which includes both ground and aerial-based drones for field checking, field well-being appraisal, plantation, water system, crop splashing, soil and field investigation, and different areas [15]. Since drones gather thermal, multispectral, and visual imagery during the flight, the gathered information gives ranchers with insights into plant count and crop prediction, plant health indices, plant height measurement, stockpile measuring, scouting report, nitrogen amount in wheat, and chlorophyll measurement.

6.7.3 Smart greenhouses

Conventional greenhouses handle the ecological parameters by a manual intervention which brings about energy loss, production loss, and increased labor cost [1]. It is automatic, smaller-scale environment controlled condition for preferable plant development [32]. Specifically, atmosphere control accomplished by locating a few sensors sends alarms regarding water or air problems [29]. IoT drives smart the greenhouse intelligently controls the screen as well as the environment, disposing of the need for manual intersection. To do as such, various sensors that measure the ecological parameters as per the plant necessity are utilized and stored it in a cloud for extra preparation and controlled with insignificant manual intervention.

For example, Farmapp and Growlink are likewise IoT agriculture items that permit accomplishing such capacities.

Farmapp offers integrated pest management software with sensor, fumigation, and observing capacities to farmers. It is also a delegate of IoT applications in smart agribusiness [29]. In particular, it incorporates an exploring application for quick recording and execution of the required measures with a similar map, satellite map, diagrams, and reports. Additionally, it is conceivable to get constant information on climate and soil condition with immediate availability to satellite pictures and algorithmic computations. At last, the usefulness of Farmapp catches improved water system. This IoT in agribusiness empowers monitoring the measure of water used upon plants for its streamlining. GreenIQ is, likewise, a fascinating item that utilizes smart agricultural sensors [33]. GreenIQ is a smart sprinklers controller that permits to deal with the water system and lighting frameworks remotely [34].

6.7.4 Driverless tractors

Tractors are a vital part of farms, and it is foreseen that these will be the absolute earliest machines changed over to driverless vehicles. As the idea of self-ruling tractors is still in the early stage, human exertion will be essential to set up the field and limit maps, characterize working conditions, and program the best field ways utilizing the path-arranging software. Also, farmers will have the duty regarding standard support and repair.

As indicated by CNH Industrial, driverless tractors will have the option to utilize comprehensive information like constant climate satellite data to use perfect conditions without human intervention [15]. The use of AgriTech has a lot of advantages in saving assets, decreasing time, cash and work, and conveying more excellent nourishment in greater amounts. Ideally, furnishing the field with AgriTech could be the answer for satisfying nourishment needs in the future.

6.7.5 Role of IoT sensors for data collection

Sensors are keenly utilized by smart urban areas to assemble significant open data. Similar sensors are presently utilized in farming to gather information identified with climate and fields. A collection of smart sensors introduced at various areas on a farm is associated with a climate station on the farm. These IoT sensors accumulate information from the Earth and transmit them to the cloud.

Some applications of the sensors include:

a) Monitoring weather conditions

The most well-known smart agriculture gadget is the weather station consolidating different smart farming sensors [34]. Particular information assembled by the sensors helps in mapping the climatic conditions. They assemble distinctive information from the atmosphere and forward it to the cloud situated over the field. The given estimations are utilized to outline climatic conditions, select the reasonable fields, and take the necessary actions to improve their ability. Utilizing the information, a farmer can screen and get bits of knowledge into precipitation occasions, wind speed and bearing, air pressure, temperature [35], and moistness. A few instances of agricultural IoT gadgets are Smart Elements, allMETEO, and Pycno.

Moving according to the climatic conditions, significant yields, and the measures to improve their development limit can be taken. It is also called precision [36] farming. By better utilization of the information, farmers can likewise quantify the danger of infections in crops, which is one of the basic issues that lead to harvest reduction. Sensors can assist in screening the crop development and well-being and any inconsistencies to prevent diseases or pervasions that can hurt the field viably. It aids in decreasing time, work, and cash bringing about higher incomes.

b) Autonomous irrigation

Subsurface drip irrigation (SDI) is a far-reaching water system method that empowers farmers to direct when and how much water their crops receive. Subsequently, when the SDI framework is coordinated with advanced IoT sensors to monitor moisture levels and plant well-being continually, farmers should intercede just when required. Otherwise, the framework will continue working by itself. This, likewise, assists farmers in utilizing a valuable asset, for example, water, ideally.

c) Monitoring and managing cattle

Other than observation of yield and climate conditions, IoT sensors accumulate information pertinent to animals utilized on a farm. For instance, Cowlar conveys smart sensors as wearables for cows. These sensors give information including health, temperature, movement, and nutrition insights on every individual's dairy animal just as aggregated information related to the herd.

6.7.6 Precision livestock management

On account of precision agriculture, smart farming methods empower agronomist to more readily screen the necessities of each animal and modify their food correspondingly, preventing disease and improving group well-being. IoT in farming helps in following the condition of the group, concerning the domesticated animal's control **[**29**]**. There exist some applications that decide the health of creatures, discover their area, and monitor the condition of pregnancies, particularly during managing cattle and chicken. Besides, large ranch proprietors can use remote applications of IoT to screen the area, prosperity, and strength of their cattle. Through this data, they can distinguish creatures that cleared out for separation from the group, and prevent the circulation of disease. SCR by Allflex and Cowlar are examples among IoT applications in farming. SCR by Allflex offers dairy animals, milking, and group knowledge. Cowlar is an organization that tends to the comparative needs – improving milking, increasing performance, and decreasing work costs – alongside boosting production.

6.7.7 Autonomous agricultural robots – Agbots

Robots are progressively being deployed in different enterprises to remove human blunder as well as work. Cultivation is a work-escalated job with its majority involves redundant and normalized task. It is a perfect area for robotization and mechanical technology. Agbots is the smart farming method which will open prospects to deliver better nourishment with less human work. They are beginning to show up on farms performing assignments from planting and watering to reaping and arrangement [15]. Some of the jobs performed by Agbots are crop maintenance and harvesting.

6.7.8 Supply chain in agriculture

IoT empowers utilizing radio-frequency identification, GPS, and other zone-based sensors to handle storage and movement of plants. In view of this aspect, it can expand its adequacy, which means enhancements as far as straightforwardness and client awareness. Moreover, end-to-end ranch management frameworks are likewise a zone of the enthusiasm for IoT software advancement in cultivating a market. There exists a likelihood to introduce sensor and gadget that can give information to the investigation, reports, and bookkeeping in this unique situation. The specific solutions with these highlights are FarmLogs and Cropio. FarmLogs depicts a product for encouraging grain showcasing choices on the agribusiness market. In particular, it gives a toolbox important to making a grain showcasing plan. Cropio is the answer related to handling field management and vegetation control framework working. In particular, it encourages monitoring the condition of various fields, gives constant information on the vital updates, and helps with estimating. Among its key highlights, the capacities to give instant alerts, soil moisture, field history, vegetation map, and harvest forecast are impressive.

6.8 Benefits of smart farming

Innovations and IoT can possibly change farming from numerous angles. To be particular, IoT can improve agriculture in five different ways [33]:

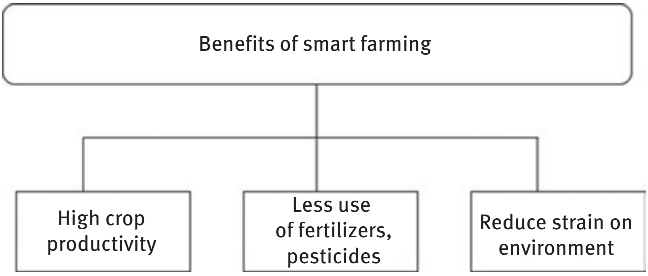

Figure 6.7: Benefits of smart farming.

- A large amount of information is collected by smart agriculture sensors, such as climatic condition, field development progress, quality of soil, or cattle well-being. This information is used to follow the business condition in general as well as the performance of staff and proficiency in hardware.
- Better authorities within the strategy, therefore, reduce the production risk. The ability to foresee the harvesting of crop permits to show signs of improvement for item dissemination. In the event that is known particularly about how much crops are going to reap, then ensure regarding an item that it would not lie.
- Depletion in residual products and monetary management on account of the expanded command overproduction. With the choice to perceive any problem in the crop production or domesticated animal's well-being, then the option will be to moderate the danger of unsuccessful crop.
- Enterprise productivity improved by procedure mechanization.
  Numerous procedures automated over the development cycle such as fertilizing, pest control, or irrigation by utilizing smart gadgets.
- Improved quality and quantity of product.

To accomplish better control on the production method and keep up development limit with better expectations of field quality [34].

Accordingly, such factors can inevitably prompt a higher income.

6.9 Effects of AI and IoT on the environment

IoT and artificial intelligence (AI) solutions can incomprehensibly improve crop yields and might be the best way to accomplish a superior framework according to few specialists [37].

6.9.1 Precision farming through microsensors

Most cultivating activities require a sharp eye, as farmers filter their yields for indications of disease and contamination. At a full-scale level, the procedure is simple, yet the eyes cannot spot everything. With the assistance of present-day IoT arrangements, also with mobile computing and AI, farmers can counterbalance the whole procedure, depending on innovation to do the audit. Farmers can screen individual plants for potential disorder and sickness with the assistance of smaller scale sensors. Also, the innovation can show details remotely through mobile or comparable gadget, permitting farmers to see instant alarms about what is going on in their fields, regardless of whether it has to do with pests, illness, or something different. Numerous sensors are as of now being used in the present market, from mechanical sensors that measure soil compaction and disintegration to continuous gadgets that identify pest populaces.

6.9.2 Drone operations and crop monitoring

Alongside IoT observation – or maybe instead of it – aerial drones can examine and screen the crops. Drones accumulate data about plants down to a solitary leaf by utilizing cameras and sensors which implanted inside. The detailed picture of a farmer's stock is given by all gathered information at that point when taken care of into a neural system or machine learning solution.

6.9.3 Smart collars for livestock

Cattle and livestock management is no little accomplishment. In addition to the fact that farmers have to screen every animal's whereabouts precisely; however, they likewise need to remain in touch about their well-being. To reduce a portion of the obligation, farmers have started furnishing their dairy animals with Fitbit-like IoT wearable that screen the information in real time. Wearable applications can be utilized on any animals on a farm, including ponies, dairy cattle, and poultry.

6.9.4 AI-powered pesticide applicators

Farmers can more readily shield crops from bugs by joining AI control arrangements and IoT sensors. Spot treatment permits farmers to treat plants separately and stay away from potential bugs. Simultaneously, less synthetic substances enter the nearby condition, including the soil underneath.

6.9.5 Smarter operations through data sharing

- The information sharing of thousands of arrangements and applicable measurements can make for increasingly powerful activities in the farming world.
- Farming specialists can share and consume a huge measure of information through data sharing like everything from soil and seed tests to yield-improving support tips.

6.10 The downside to modern technology

IoT and AI will undoubtedly have a noteworthy effect on farming. These tech advancements, however, accompany some potential setbacks, for both farmers and the environment [37]:

- Increased cybersecurity risk
  As innovation keeps on depending on the web – and more activity, explicit information is gathered – vulnerabilities and access points will appear. Thieves can take more than delicate data. In the event that IoT arrangements set up, remote programmers can hold onto control of uses. When a programmer was to deal with a pesticide dispersal framework, for instance, it could demonstrate terribly. Hypothetically, they could shower a greater number of synthetic substances than required, harming or slaughtering crops. Then, farmers must execute digital security to prevent them from potential attacks.
- High adoption cost
  IoT empowered gadgets and sensors, while not amazingly costly but when purchased in mass can demonstrate expensively. An appropriate local network, along with the hardware, must be set up to encourage and support the massive flood of information. Besides, there is the matter of appropriate information stockpiling, either locally or cloud based. Big data and AI solutions should likewise be actualized on the backend to investigate, sort out, and extricate usable knowledge from advanced content. These prerequisites can prompt unbelievably high appropriation costs at even the littlest of agrarian support.

– Environmental risks
  A framework that underpins an enormous scope of rural activity will require large measures of vitality. To exacerbate the situation, all-new innovation expects capacity to run. Besides, many propelled robots arrangements despite everything need petroleum products to work, polluting the atmosphere. Without increasingly supportable vitality or even sustainable arrangements, IoT and present-day comparative advancements are not a legitimate fix for ecological issues. Rather, consideration may mess more issues in the short interval.
– Farmers and makers as of now use IoT and AI innovation to increase operational efficiency and decrease waste yield. From sensor monitoring and drone to Fitbit-like wearables, the developments appear to be unending. As smart gadgets complete routine undertakings, farmers can invest more energy in basic issues, for example, lessening discharges and their ecological effect.
– For the agricultural industry, technology has considered as a boon, yet it is additionally observed a few downsides too. Steep price tag often results in increased efficiency, a cost that some small-scale farmers cannot bear. Also, gadgets that a sudden spike in demand for petroleum products further add to environmental change. The truth will surface eventually what jobs AI and IoT play later on.

6.11 Conclusion

Agribusiness is demographically the broadest monetary locality and considers a critical job in the overall general budgetary texture of India. Agriculture mainly relies on the traits of soil and irrigation water. Traditional cultivation systems are unable to give a better result due to the change in weather and climatic conditions as they rely on old beliefs. Proper irrigation has been done to acquire better results. With the advent of technologies like IoT, the newer technologies are replacing the previous methodologies, which result in bringing about a widespread improvement in the terrain. Now, in the state of automation where the improvement of smart innovations are upgrading on a daily basis in almost all sectors initiated from vehicles, smart homes, garbage, farming, health, industries, grids, and so on. No doubt, the latest developments in technology have a great influence on farming. IoT-based smart farming can likewise increase the value of developing trends agriculture like family farming, organic farming, and many more.

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7 Internet of things platform for smart farming

Abstract: Internet of things (IoT)-based smart farming is a mechanism initiated with various sensors to monitor the temperature, soil pH, moisture, and so on of the farm and automate the irrigation system to provide high quality and quantity of agricultural products. Innovative smart farming applications will enhance the productivity with reduced wastage, efficient farm vehicle routes, and optimal fertilizer usage. The benefits and technologies required for implementing smart farming are initially focused in this chapter. Then, the role of IoT in transforming the agriculture; cases where IoT is used, for example, precision farming, agriculture robotics and drones, livestock monitoring, smart greenhouse, smart irrigation technology, farm management information system, weather monitoring system (WMS), smart logistics and warehousing, waste management; and solutions to agricultural issues are analyzed. With novel end to end intelligent process and advanced business process execution, the products will reach the supermarkets in the fastest time possible with less operational cost and increased product value. This real-life implementation of IoT solutions in agriculture will perfectly demonstrate the growth of global smart agriculture into remote areas and highlight the benefits that are achieved.

Keywords: Internet of things, smart farming, livestock monitoring, precision farming, agriculture robotics, farm management information system, drones, smart greenhouse, smart irrigation, smart weather monitoring system, smart logistics and warehousing, waste management

7.1 Introduction

Agriculture is the mainstay of the Indian economy. Still in India, the agricultural practices carried out are largely traditional. More than 50% of the world population performs traditional agriculture to primeval style of farming that involves the intensive use of instinctive method, conservative tools, innate resources, organic fertilizer, and intellectual beliefs of the farmers. Traditional farming only exploits labors

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https://doi.org/10.1515/9783110691276-007

for tilling, sowing, and harvesting. Irrigation mainly depends on rain, and seeds used are not contemporary. It produces high-quality healthy products in smaller quantities with the usage of biological pesticides and insecticides. Besides, various factors reliable for traditional agricultural backwardness are:

- Lack of appropriate irrigation system
- Lack of transport and marketplace
- Unscientific and autocratic distribution of land
- Over manpower pressure
- Poor financial background
- Lack of research activities

Recent statistics state that the global population is about to reach 9,600 million in the next 30 years. Agriculture industry is bounded to espouse promising technologies to eradicate extreme weather conditions, climate changes, and ecological impact so as to feed this massive population. Farmers have to face many challenges to produce more food on fewer acres of agricultural land. The top issues that impact agriculture are:

- Commodity supply for rising global demand
- Cost and availability of land for extension
- New government approvals and rules
- Fluctuations in global financial markets
- Impact of universal trade rules on food security and supply

Technology is renovating almost every aspect of our modern lives. Modern agriculture includes agricultural innovations and farming practices that help agronomists to increase the efficiency with minimum usage of natural resources like land, water, and energy essential to meet the world's food, fuel, and other needs. The main benefits of technology usage in agriculture are advancing crop production rate and crop quantity, which in turn will cut down the cost of manufacturing for cultivators and food cost for users, and even makes crops more nutritious and cattle better quality.

Information technology is a potential tool enriched with novel technological ideas and innovations in farm management for yield increase and enhanced resource allocation. The late nineteenth century has brought a number of mechanical inventions like harvesters and tractors. Exploitation of satellite and agronomy technologies will increase the agricultural production. With that in mind, the technologies that can modify the farming setting in the years ahead are:

- Soil humidity and water sensors
- Weather tracking
- Satellite imaging
- Pervasive automation
- Mini chromosomal technology

– Radio-frequency identification technology
– Vertical farming

AgriTech refers to application of technology to agriculture. In smart agriculture with intelligent operations and process execution, crop production gets processed faster and reaches the markets on time with high product value and less operational cost. *This chapter explicates the real-life adoption of Internet of things (IoT) solutions which will perfectly point up the expansion of large-scale smart agriculture into remote areas and emphasize the benefits that can be achieved with the exploitation of latest technologies.*

7.2 Smart farming

Smart farm is a farm coped with modern information and communication technologies to optimize the production of agricultural products. Smart farming deems that it is essential to concentrate on the issues of population growth, climate and weather changes, and labor requirement from crop planting to harvesting. By exactly measuring the variations within the field and adapting the strategies accordingly, farmers can significantly elevate the selective efficient use of fertilizers and pesticides. Smart farming techniques can also enable farmers to monitor the needs of farm animals, regulate their diet accordingly, and enhance the herd health by restraining disease.

IoT in agriculture has risen as a second wave of green revolution. Smart devices and sensors incorporated on farms make farming processes more data-driven and data-enabled. IoT-based smart farming monitors the field in real time and helps farmers to take right decisions to decrease their production costs and increase yields.

7.2.1 Technologies required for smart farming

Though smart devices support the amplification of the farm's revenue and performance in many ways, the development of IoT-depended farming applications are still not the easiest task. Prepared with all feasible tools, the farmer can monitor the field conditions and make strategic decisions without even going to the field. A fully endowed smart farm requires

– *Sensors*: To examine the quality of soil, water usage, temperature, and pressure
– *Software*: Suitable procedures to run the farming
– *Connectivity*: Need of cellular network, LoRa network, and so on
– *Location*: Farmers can track the location of their equipment, livestock, or packaged products with global positioning system (GPS)

- *Robotics*: Usage of modern autonomous processing equipments
- *Data analytics*: Techniques for data collection, data analysis, and strategic decision-making

7.2.2 IoT-based smart farming system – workflow

Though the operations of smart farm are identical to any other farm, more advanced possessions happen in smart farm. The workflow of IoT-based smart farming system involves three phases: *sensing*, *processing*, and *information distribution*.

In *sensing* phase, the real-time environmental characteristics of soil, air, and water of the field are sensed and transferred to the gateway. IoT gateway congregates data from all the sensors and transmits it to the cloud for further processing. The obtained data are visualized as graphs, histograms, and so on [1].

In the next phase of *processing*, data on the cloud are processed to create a number of multipurpose results. For example, proper irrigation schedule, which will help the farmer to increase the crop yield, is generated by monitoring the weather data. Real-time values on the cloud can be compared with these threshold values and weather data. If these values are greater than the threshold values, then the requirement of irrigation can be decided [2].

Information distribution is the last phase of this system. The generated schedule of irrigation and real-time data collected from the field are displayed on the mobile application in more explicable and readable form so that farmers can see and take appropriate action.

The different phases of smart farming cycle are:

Observation: Sensors are used to observe and record the data related to crops, livestock, soil, or atmosphere.

Diagnostics: The observed sensor values are diagnosed with predefined decision rules and models.

Decisions: The user and IoT components conclude whether the location-specific treatment is essential or not.

Action: The cycle repeats from the beginning once the end-user evaluation and action are completed.

Example:

Let us consider the following situation to get a better idea on how the smart farm cycle works.

Let the farmer have a problem with reduced crop yields, and to realize the issue, he/she tries to use IoT sensors to study the soil.

Figure 7.1 explains the study of this soil composition situation [3]. Once the crop yield is poor, the soil composition is studied with the data captured by IoT sensors, analyzed, and recognized to determine whether the soil is suitable for that particular type of crops or not. This process will be carried out on various fields to identify the most suitable soil and conditions for increased crop yields of that particular crop type, that is, identification of suitable soil field for the specified crop type will be performed with the help of IoT-based smart farming technology.

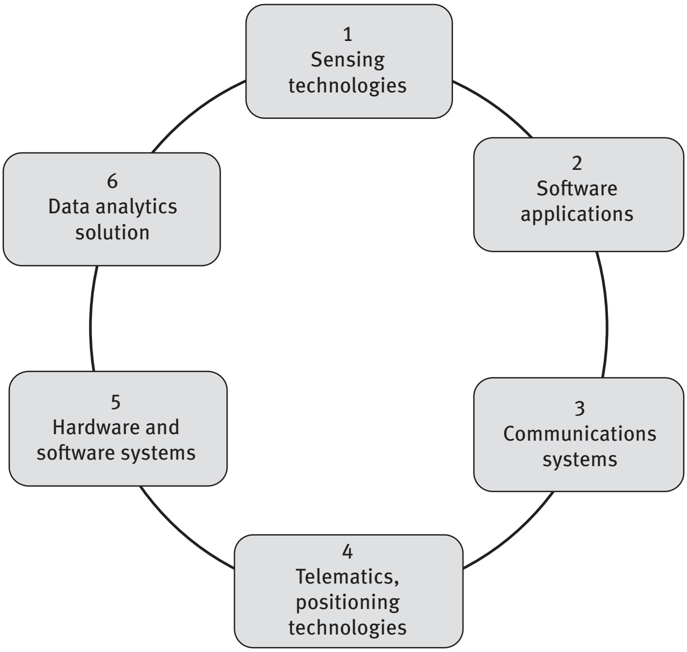

Figure 7.1: Smart farming cycle – soil composition.
Source: (HQ Software, Boost Your Farm's Yields with IoT-Enabled Smart Farming, *Internet of Things, 2019)* [3].

7.2.3 How IoT is transforming agriculture?

The different ways with which IoT applications transform and improve the traditional agriculture are:
- *Data collection:* Massive data on weather conditions and soil.
- *Internal process control and lower manufacturing risks:* Predicting the production output for better product supply.
- *Cost and waste reduction management system.*
- *Process automation:* Enhanced product quality and volume with the automation of irrigation, fertilizing, or pest control processes.

- *Remote control:* To control equipment from a distance. Usage of drones to sense water and nutrient deficits, analyze soil and weather conditions, and assess ripeness of crops.
- *Pest control:* Lets farmers spot pest-infested crops and weeds with infrared cameras.
- *Irrigation*: Able to remotely monitor soil moisture, water levels, and water conservation.
- *Mammal tracking*: Employing sensors to monitor the location of the roaming animal herds.
- *Supply chain management*: IoT sensors can facilitate the industry to keep track of their produce from farm to fork, ensuring that the significant standards are adhered to, habitually monitored, and never breached [4].

The role of IoT in smart farming is shown in Figure 7.2.

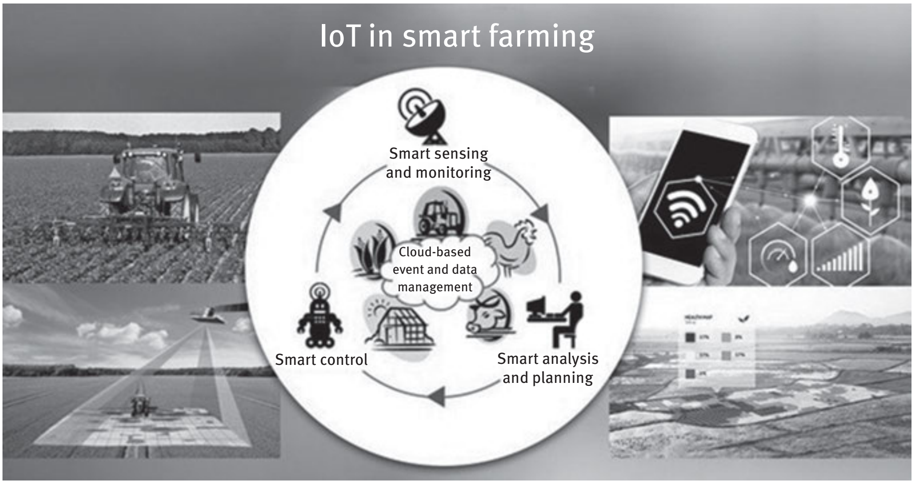

Figure 7.2: IoT in smart farming.
Source: (Rohit Sharma, A review on use of big data in warehousing to enhance the accessibility of food, 2017) [5].

7.3 Precision farming

Using satellite imagery and sensors to congregate data for the intention of improving production output, minimizing cultivation costs, and preserving resources is defined as precision agriculture (PA). Its goal is to assure profitability, sustainability, and protection from the environment. It depends on certain materials like software and IT work providers to access real-world data about the crops, labors, soil, equipment availability, and environmental factors. The field sensors are employed to measure the moisture content and temperature of the soil and surrounding air. The plant images captured by the satellites and robotic drones are processed and integrated with other agricultural control center's sensor data to enrich the farmer's skill in identifying the fields that entail treatment and determining the optimum usage of water, relevant fertilizers, and pesticides. This facilitates the farmer to evade wasting resources, prevent run-off, and ensure that the soil has the right amount of additives for optimum health with reduced cost and farm's environmental impact.

The plants and farm animals will get the treatment they need precisely with staggering accuracy. The farmers can take intellectual quick decisions based on sensor data generated on per square meter area or even per plant/animal rather than for a field in precision farming (Figure 7.3) [6].

Figure 7.3: Precision farming.
Source: (precisionagricultu.re/wp-content/uploads/2014) [7].

GPS and remote sensing technologies support farmers to realize the input needs and required quantities of inputs which let them to use expensive resources such as fertilizers, pesticides, and herbicides, and water resources effectively. Due to this, farmers can maximize their yields and increase their profits with minimum operating expenses. The significant role of geospatial technology in precision farming is shown in Figure 7.4.

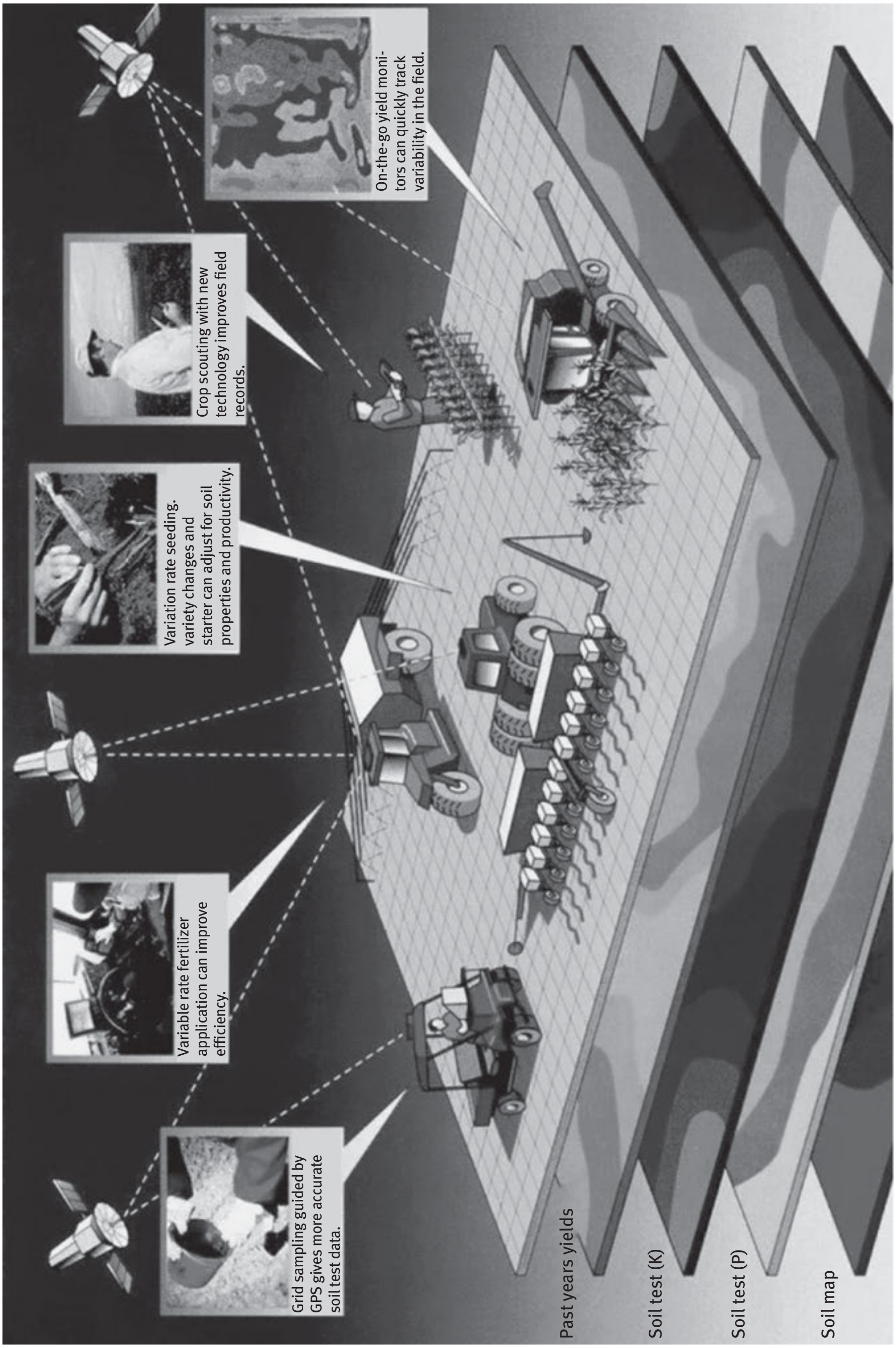

Figure 7.4: Role of geospatial technology in precision farming.
Source: (Peter Rodericks Oisebe, Geospatial Technologies in Precision Agriculture, GIS Learning, 2012) [8].

7.4 Agriculture robots and drones

Robotics, a subset of PA technologies, is employed in all points of crop yielding starting from soil evaluation to ploughing/seeding to harvesting and packaging. In small-scale high-profit-margin agriculture, highly accurate GPS-based copious robots are nowadays utilized to automate slow, repetitive, and tedious tasks to improve the overall production yields [9]. The simple agricultural robot is shown in Figure 7.5.

Figure 7.5: Agriculture robots.
Source: (en.wikipedia.org/wiki/ Agricultural_robot) [10].

Agricultural robots are classified into outdoor and indoor robots based on the usage. The robots were designed to perform various tasks like spraying, weeding, fruit harvesting, autosteering, and autonomous navigation, and their usage is shown in Figure 7.6. The robots are trained with weed images to recognize and pluck weeds or directly apply pesticides on the weed itself and not on the entire plant. In addition, they are able to harvest fruits without damaging them. Indoor agriculture robots are used for greenhouse harvesting and material handing [11].

Agricultural drones are unmanned aerial vehicles that make use of big data and aerial imagery to optimize efficiency. They offer potent data processing ability afforded by cloud-based computing to carry out aerial monitoring, inspection, and intelligence-gathering capabilities. The farmers can collect data on plant level and generate suggestions on square meter level instead of field level. The drones can be operated via drone-as-a-service-type operation with premeditated flyovers or can be laid on site and exploited as needed with weatherproof docking stations that permit the drones to refresh and send data back to be analyzed. One of the simple agricultural drones is shown in Figure 7.7.

Figure 7.6: Outdoor agriculture robots: (a) spraying and weeding robots, (b) auto steering, (c) autonomous navigation, and (d) fruit harvesting robotics.
Source: (*posts capes, outdoor-robots, 2018*) [11].

Figure 7.7: Agriculture drone.
Source: (DJI Enterprise White Paper, DJI's agriculture drones, *2019)* [12].

The ground-based and aerial drones are incorporated in smart farm for crop stem leaf and flower monitoring, autospraying, autoplanting, automatic soil testing, and other spheres. The multispectral visual imagery data collected by drones provide farmers with the complete insights of plant health indices, plant counting, yield forecasting, plant height, field water tarn mapping, review reports, supply measurement, chlorophyll measure, nitrogen content, drainage mapping, and so on [13]. The usage of agriculture robots and drones in smart farming are summarized in Figure 7.8.

Figure 7.8: Agriculture robots and drones.
Source: (Jyotsana Chuchra, Drones and Robots: Revolutionizing Farms of the Future,2016) [14].

7.5 Livestock monitoring

Animals in a farm together are called livestock. Livestock monitoring helps farmers to track their cattle to recognize when they are feeding and drinking, their temperature, humidity, and heartbeat in an easier and efficient way. Animal ailments will be closely monitored and ample preventative measures will be taken much earlier. An IoT solution provides key insights in most aspects of farming livestock. The simple livestock management system is shown in Figure 7.9.

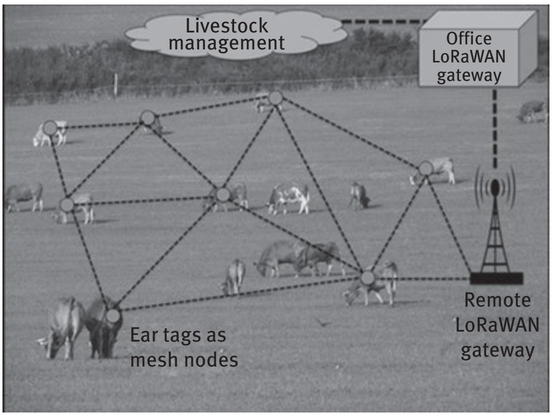

Figure 7.9: Livestock monitoring.
Source: (Braemac, IOT AND LORAWAN MODERNIZE LIVESTOCK MONITORING, 2016) [15].

7.5.1 Role of IoT in livestock monitoring

7.5.1.1 Livestock real-time health monitoring

Since farmers lose considerable amounts of profit due to animal illnesses, IoT-enabled livestock management solutions are available to endorse better livestock health. Sensors are mounted with livestock wearable to monitor heart rate, blood pressure, temperature, respiratory rate, digestion level, and so on. Farm animal tracking is helpful in skating the sick animals as well as implementing and reducing the rumination patterns [16].

7.5.1.2 Monitoring reproductive cycle

An IoT device connected on a cow can monitor and measure when it goes into heat, as they can be in heat for about 8 h. IoT-enabled monitoring totally removes the need of supervising cows manually for the calving process and encourages safer and successful births [17].

7.5.1.3 Location tracking

Without hassle, farm animals can be traced out in no time with the assistance of IoT wearable. Moreover, sensors integrated into IoT device can alert the farmer when cattle's activities appear to be changing.

7.5.1.4 Maximizing livestock livelihood

By monitoring the cattle behavior, the farmer can simply identify if the cow has to be milked at that time, milking amount, and speed. The wearable controller with sensors fetched in the animal's neck finds the exact lactation, the consumption of food by the cow, and the distance walked per day [17].

7.6 Smart greenhouse

Smart greenhouse is a great revolution in agriculture industry (Figure 7.10). It creates an independent microclimate suitable for automatic plant growth using sensors, actuators, and monitoring and control systems. Greenhouse proffers controlled environment for optimum cultivation of crops. On the other hand, weather changes and "invisible" conditions like open doors or early-stage infection frequently influence the greenhouse environment and intimidate to damage crops [18]. Due to ineffective monitoring and control of the factors like light, air, and temperature, many farmers fail to attain good profits and desired yield from greenhouse crops [19, 20].

Figure 7.10: Smart greenhouse.
Source: (Smart Greenhouse: The future of agriculture, 2016) [20].

To overcome the disputes faced in traditional greenhouse, smart greenhouses are equipped with present sensor and communication technologies to capture and deliver crop information automatically. Collected data are provided into an IoT platform where it is analyzed by appropriate software to expose the bottlenecks and deformities [18]. As a result, the heating, ventilation, and air conditioning; lighting; irrigation; and spraying activities can be fine-tuned on demand. Continuous data monitoring supports the progress of predictive models to gauge crop disease and infection risks.

7.6.1 Key components of smart greenhouse

Let us consider a smart greenhouse tomato crop growth, where the following parameters are monitored and controlled to ensure better growth rate:
1) Luminosity
2) Temperature
3) Soil moisture
4) Humidity

Farmer can understand the plant growth cycle, monitor the farming factors, and take proactive measures if any of the following factors are distressed [19]:
a) Monitoring nitrogen to quantify the bulge of the produce
b) Phosphorus paucity to estimate soil fecundity
c) pH value
d) Lycopene inspection to obtain the insights of product color variations
e) CO_2 level of a crop

7.6.2 Benefits of smart greenhouse

7.6.2.1 Creating right atmosphere for better crop yield

To increase the value of crops, smart greenhouse farmers can form climate-smart and nutrition-sensitive atmosphere for their crops.

7.6.2.2 Correct water usage

Water conservation is ensured by setting a schedule based on the type of crops, quality, yields, and weather parameters [19].

7.6.2.3 Observe resource consumption

To measure energy consumption for optimal resource usage, smart greenhouse employs an automatic control system containing network sensors to continuously monitor and calculate the run-off.

7.6.2.4 Automate plant growth monitoring

Permits cultivators to examine the parameters essential for healthy growth of a crop, send alert messages when there is a difficulty, and manage the greenhouse activities with remote devices. This will enrich the following strategic benefits:
- Monitor parameters for anomaly
- Control environment for improved yield
- Save power, electricity, and water consumption

7.6.2.5 Maintain ideal microclimate conditions

Let the farmers collect real-time climate data like temperature, humidity, light exposure, pH, soil capability, and CO_2 level of the greenhouse with IoT sensors at various levels.

7.6.2.6 Enhance irrigation

Smart greenhouses facilitate farmers to inhabit on top of their crop conditions to assure that irrigation and fertilization activities are on par with the real requirements of the farmed plants with highest yields; readings on soil volumetric water content designate whether the crops are under water stress or not [18].

7.6.2.7 Fertilization practices

Based on the measurements of soil salinity, sprinkler and spraying methods can be involuntarily turned on to tackle the real-time crop demands.

7.6.2.8 Prevent thefts and security improvement

Many growers do not have an effectual security system due to expensive traditional surveillance networks. IoT sensors in smart farmhouses with peak-valued plants propose an affordable mechanism to monitor door status and detect apprehensive activities. With an automated alarm system, they instantly notify the growers when a security issue arises [18].

7.6.3 Indoor environment monitoring – smart greenhouse

The indoor smart greenhouse parameters are:
- Adjust the color output during the plant lifecycle
- Drill down to light settings and mutate LED color for reliable end-product quality
- Monitor the performance of growth environment
- Fine-tune the plant's growth strategies to improve crop production.

Monitoring the indoor smart greenhouse parameters is shown in Figure 7.11.

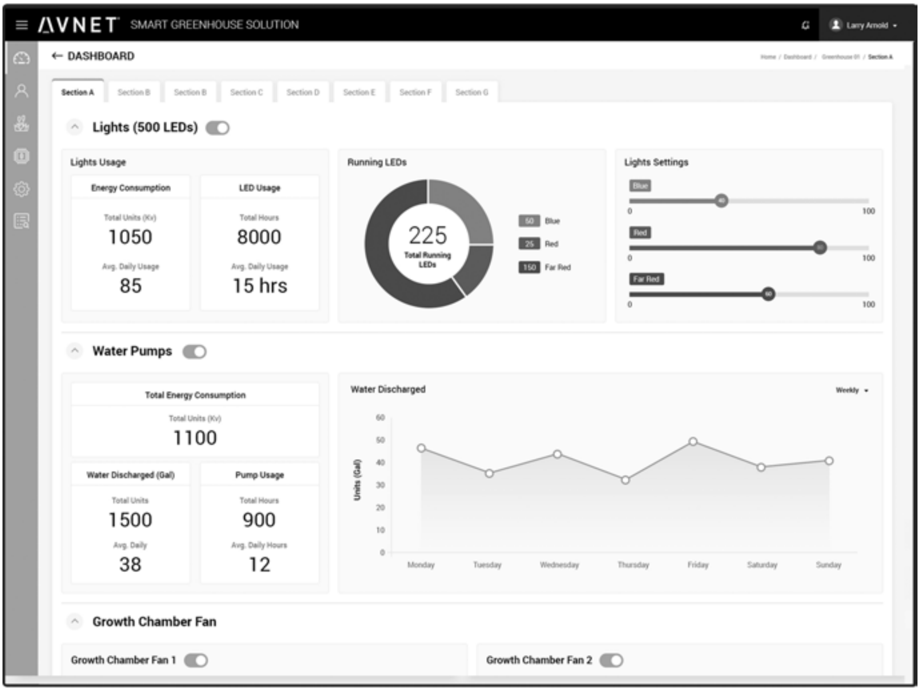

Figure 7.11: Indoor smart greenhouse monitoring.
Source: (IoTConnect, Smart Greenhouse) [21].

7.7 Smart irrigation system

Analyzing the humidity of soil and climate conditions automatically in farming using an IoT-based device is known as smart irrigation system (Figure 7.12) [22]. The watering schedule can be regulated automatically by monitoring the weather, soil conditions, evaporation, and plant water usage. Controlling the plant water usage improves sustainability, reduces manufacturing costs, prevents disease and weeds, conserves water and time, and also preserves soil composition and nutrients.

The farmer can start off the motor or not by just using a single application. Once the motor pump is started,

1. The farmer can switch off the motor.
2. The motor pump is automatically switched off when the soil moisture sensor value reaches the required threshold parameter value.
3. Finally, if there is a rain in the field, the microcontroller will automatically shut down the motor pump till raining and checks whether the soil moisture sensor has sensed the consequent threshold value or not. The motor pump will remain shut down if it crossed the required threshold value. Otherwise, it will start

Figure 7.12: Smart irrigation system.
Source: (Disruptordaily,tevatronic-smart-irrigation) [23].

again without any human intervention. This process helps in saving water and electricity consumption.

4. The motor switched off due to power shutdown is automatically restarted when the power supply is available.
   Figure 7.13 shows this smart irrigation process.

7.8 Farm management information system

Farm management information system (FMIS) is a management information system devised to support the farmers to decide on how the farm activities will be planned, categorized, resources shared out, and performed field works are documented [24]. It deals with a variety of information policies and methods to optimize and control farm operations and production activities to keep a farm more fertile.

7.8.1 Knowledge base of best practice processes

An expert farm manager is essential to maximize the crop yield and revenue of the farm land. He should be equipped with a knowledge of when and how to perform activities like pest treatment and fertilizer usage in field.

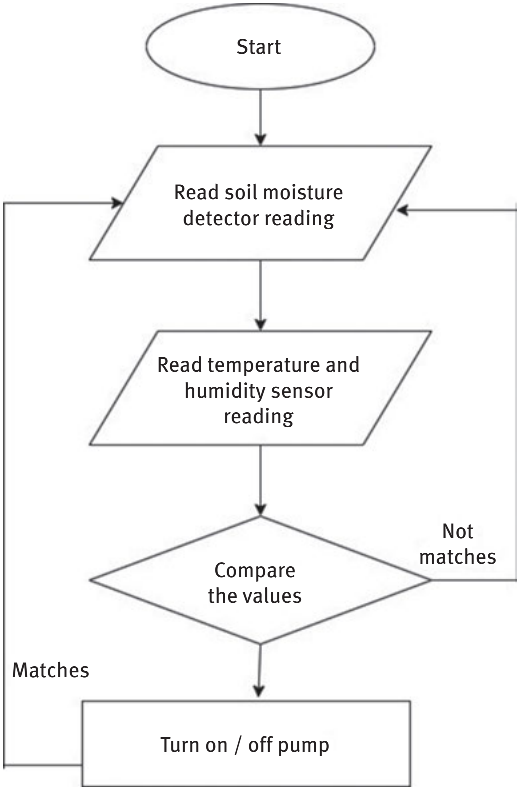

Figure 7.13: Flowchart for smart irrigation system.

7.8.2 Personal data

Farm management system lets the farmers to gather, process, stock up, and broadcast data such as land use, input cost, and product price, and where to get them. Precise personal records maintained in FMIS will assist the farmers to analyze and enhance the field details for better profit.

7.8.3 On-time information

In agriculture, factors like weather conditions, diseases, demand, supply, or market prices of the goods are far beyond the direct influence of the farmers to deal with [24]. If any adverse event occurs, it must be traceable and immediately detectable by the farm management software to avert further waste or damages. Scheduled ongoing activities must be recorded, and performance of every cost object and activity utilized has to be measured on hourly/daily basis.

A simple FMIS and its architecture from the user viewpoint are shown in Figures 7.14 and 7.15. Farm management software helps farmers to plan, supervise, and analyze all farm activities simply. With a few clicks, tilling, planting, crop fortification, irrigation, fertilization, and harvesting are handled. In addition, anyone can easily track the quantity of input usage, costs, and work hours of each activity [25, 26].

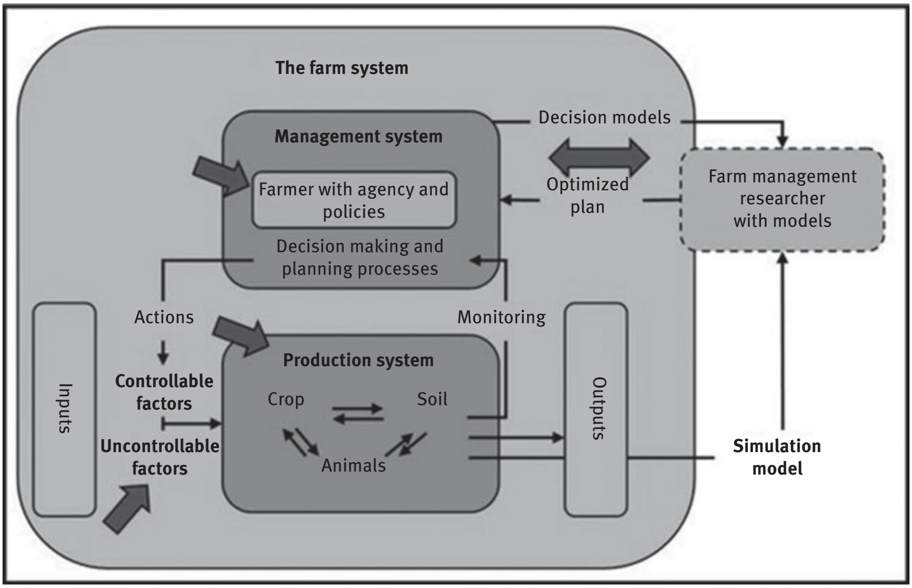

Figure 7.14: Farm management information system.
Source: (Sorensen & Kristensen, Farm Management Information Systems, 1992) [25].

PA supported by FMIS of the farm activities represents a feasible efficient solution for its modernization. FMIS focuses on land mappings, internal and external data collection, monitoring parameters, and data processing for decision support. Through FMIS, the farmer can have the ability to take better profitable decisions with the information about pioneering technology, available resources (labor and materials), market facts (competitors, prices, and forecasts), and government policies.

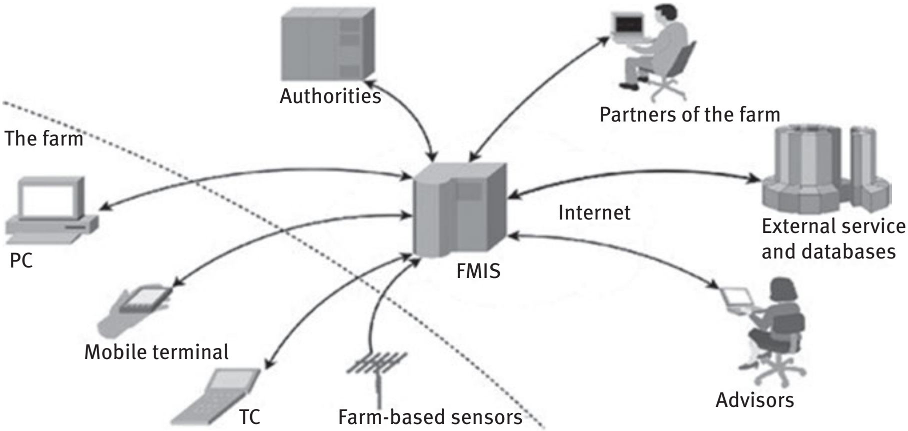

Figure 7.15: FMIS architecture from the viewpoint of the user.
Source: (Payman Salami, Hojat Ahmadi, Review of Farm Management Information Systems, 2010) [26].

7.9 Smart weather monitoring system

Crops need low and high temperatures to initiate their germination and advance the development. Temperature combined with moisture is used to predict various insect pest and disease occurrences. This will facilitate the farmers to prepare the schedule for sowing, fortification, harvesting, and to avoid yield losses [27]. Further, the weather observations will provide information about current crop growth.

Weather stations are used for precision measurement of environmental conditions to achieve healthy plants and increased yield (Figure 7.16). The types of weather stations depend on the measured parameter count, work precision, and work range [28].

Figure 7.16: Weather station in the field.
Source: (ALEX DE PAPE,Stay Tuned for Your Local Weather,2017) [28].

The parameters regarding soil and crop conditions monitored are [29]:

Rainfall: To estimate the rainfall over a period
Temperature: To track the temperature variations over a day/week/month or longer
Wind direction and speed: To perfectly forecast the looming storms
Air pressure: Upcoming weather indicator such as thunderstorm
Humidity: To take better decisions on water usage

All these measured parameters can be used for preparation of irrigation events schedule, development of pest alarm models, as well as determination of crop fertilization and protection time. Farm-based weather data guarantees sustainable farming, thus protecting the environment is more important for a successful farm management. Climate monitoring system will predict the changes in weather and climate with the aid of satellite observations, ground-based data, and forecast models. A chronological record of spot measurements statistically analyzed with the identification of mean values, trends, and variations over time are also provided. From this information, one can understand and predict the changes in weather and climate much earlier. Various work station instruments placed at specific weather station locations to compute different atmospheric surface variables over land, sea, and ice are listed in Table 7.1. At sea, weather buoys are equipped with additional devices to assess the oceanic essential climate variables [30].

Table 7.1: Weather station instruments and parameter measurements.

S.no.	Instrument	Parameter
1	Thermometer	Air and sea surface temperature
2	Barometer	Barometric pressure/air pressure
3	Hygrometer	Hygrometer
4	Anemometer	Wind speed
5	Wind vane	Wind direction
6	Rain gauge	Precipitation
7	Pyranometer	Solar radiation

7.9.1 Tasks of smart weather monitoring system

To constitute number of samples/day
To track the historical measurements over a period
To view the field sensor locations
To inspect smart dashboards with examined metrics
To utilize most excellent sensor fleet management tools
To locate open and secured data options

7.9.2 Benefits of measuring weather conditions

7.9.2.1 More precise farming

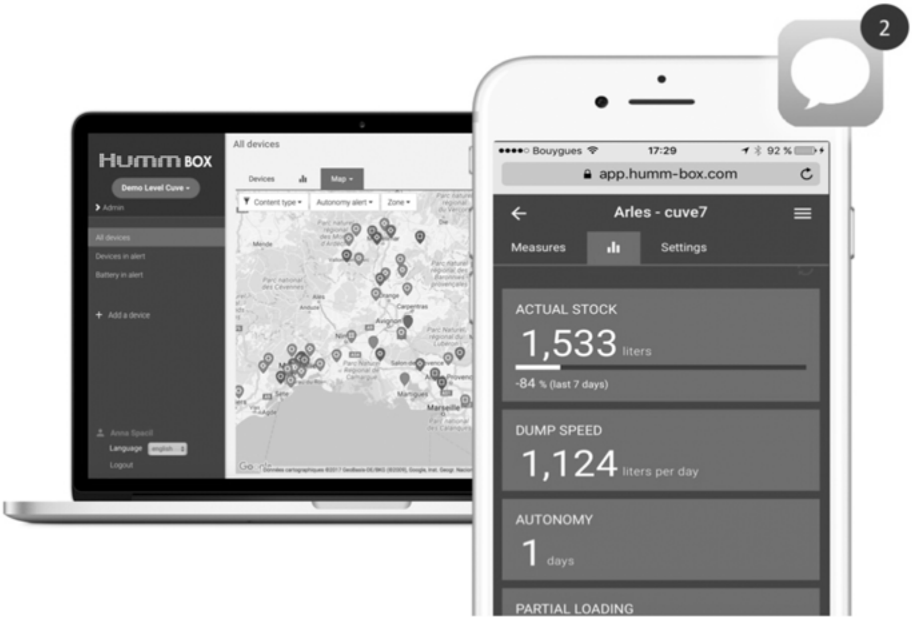

Figure 7.17: Weather monitoring system.
Source: (partners.sigfox.com/products/hummbox-iot-platform-and-apps) [36].

The weather data captured using IoT sensors makes water usage, planting, and maintenance more accurate and efficient, which can help farmers to save time, labor, and money.

7.9.2.2 Technology offers better data

Farmers can perceive and forecast imminent rainfall, humidity, temperatures, and freezes by accessing exact field weather data remotely. The benefits of weather monitoring are shown in Figure 7.18. As a whole, IoT-based weather monitoring can cut down the crop production costs, avoid over- or underwatering, and increase the crop yields.

Figure 7.18: Benefits of weather monitoring.
Source: (SIGFOX, The Agricultural Benefits of Weather Conditions Monitoring Sensors) [29].

7.10 Smart logistics and warehousing

Smart logistics affords opportunities to progress vibrant traffic management and enforcement of local rules, for example, in terms of accessibility of a city center (time of day, location, and type of vehicle). IoT in smart farming enables farmers to make sure that the environmental situations like temperature, climate, and humidity are sustained within the set levels during shipment. With intelligent technologies and cloud-based services, smart logistics system can address and examine these issues to increase the quality, quantity, sustainability, and cost effectiveness of farm production. Without human intervention, it monitors the temperature around the material and reports if any digressions are found from set thresholds. It not only represents the deviation in temperature but the period as well as locations (Figure 7.19).

Figure 7.19: Smart logistics system.
Source: (Bell.One, Smart Logistics for Agriculture) [38].

A smart warehouse is enabled with a number of automated and interrelated technologies that work together to boost up the production and efficiency of the warehouse with less number of labors. In smart warehousing, the system automatically verifies that the products are in stock when the orders are received. The pick-up lists are then mailed to robot cart which will put the ordered products into the containers for delivery. A warehouse management system (WMS) keeps track of warehouse's day-to-day and specific activities and has many uses, starting from assembling precious data to helping users to handle warehousing processes. The key elements of smart warehousing system are shown in Figure 7.20.

7.11 Smart waste management

Agricultural wastes are residues generated from the agricultural activities like cultivation, livestock production, and aquaculture. Recently, for policy makers, agricultural waste management (AWM) is a main issue of concern for natural agriculture and sustainable development. AWMS is a designed AWM system in which all vital components are accumulated and handled to manage and use the by-products in a way that prolongs or improves the quality of air, water, soil, plant, and animal resources. A simple AWMS architecture and its related functions are shown in Figures 7.21 and 7.22.

AWMS consists of six basic mechanisms: production, collection, storage, treatment, transfer, and utilization. *Production* deals with the nature and quantity of agricultural waste generated by an agricultural method. *Collection* refers to the preliminary capture and congregation of the waste from the starting point to collection point. The AWMS plan has to identify the collection process, collection spots, schedule and requirement of labor, and important equipments and their executive and setup costs. The *storage* is the provisional containment or holding of the waste that affords control over arrangement and timing of the functions such as treatment and use of the waste that could be distressed by weather or some other operations. AWMS also has to identify the period of storage, quantity, nature, location, scheduling cost of the storage service, management cost of the storage method, and the impact of storage on the constancy of the waste. Waste *treatment* is the process devised to diminish toxic waste by incorporating physical, chemical, and biological treatment and increase its valuable use. It also includes the analysis of waste characteristics before treatment; determination of yearning waste features after treatment, type, estimated size, place, and setup; and execution costs of the treatment system.

Transfer refers to hauling of waste from the collection to utilization stage either as a solid, slurry, or liquid depending on the total concentration. *Utilization* specifies the valuable use of agricultural waste. It includes recycling reusable waste produces and reintroducing nonreusable wastes into the environment, energy, feeds of animal, and plant health nutrients (Figure 7.22) [40, 41].

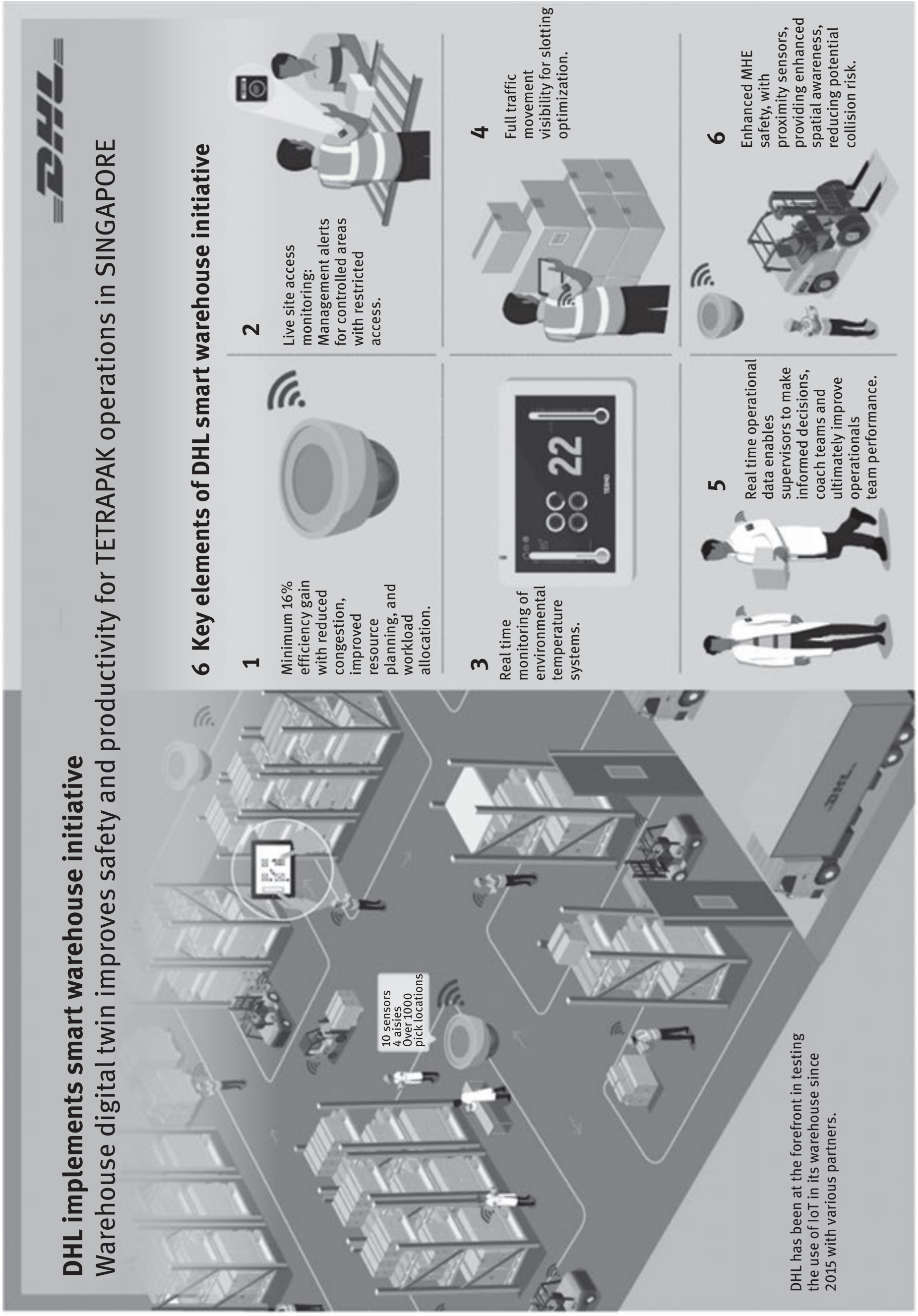

Figure 7.20: Smart warehousing system.
Source: (DHL Supply Chain, SMART WAREHOUSE WITH INTERNET-OF-THINGS TECHNOLOGY, 2019) [39].

IoT-based AWMS transforms the agriculture wastes into useful materials for human and agricultural usage managed well with IoT-based AWMS. Proper waste exploitation will support the development of agricultural sector and provide numerous doable biofuel resources Figure 7.21.

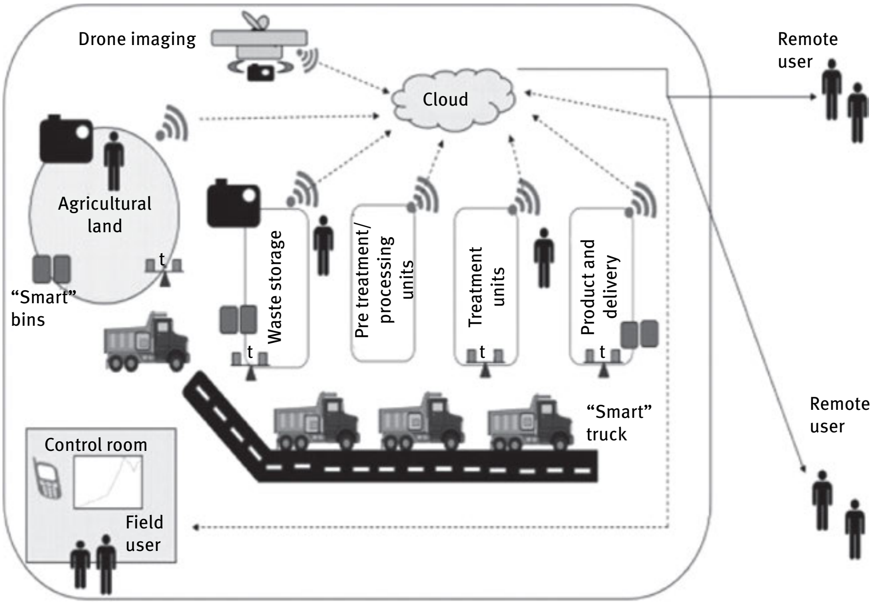

Figure 7.21: Block diagram representation of AWMS.
Source: (Agricultural Waste Management Field Handbook) [40].

7.12 Challenges in smart farming

Significant challenges that the farmers can face in adopting IoT-based smart farming are:

Building necessary digital infrastructure
Poor internet coverage in rural areas
Regularity of interfaces
Manufacturers compatibility
Quality of algorithms used
Data protection and data independence
Media competency of the farmers

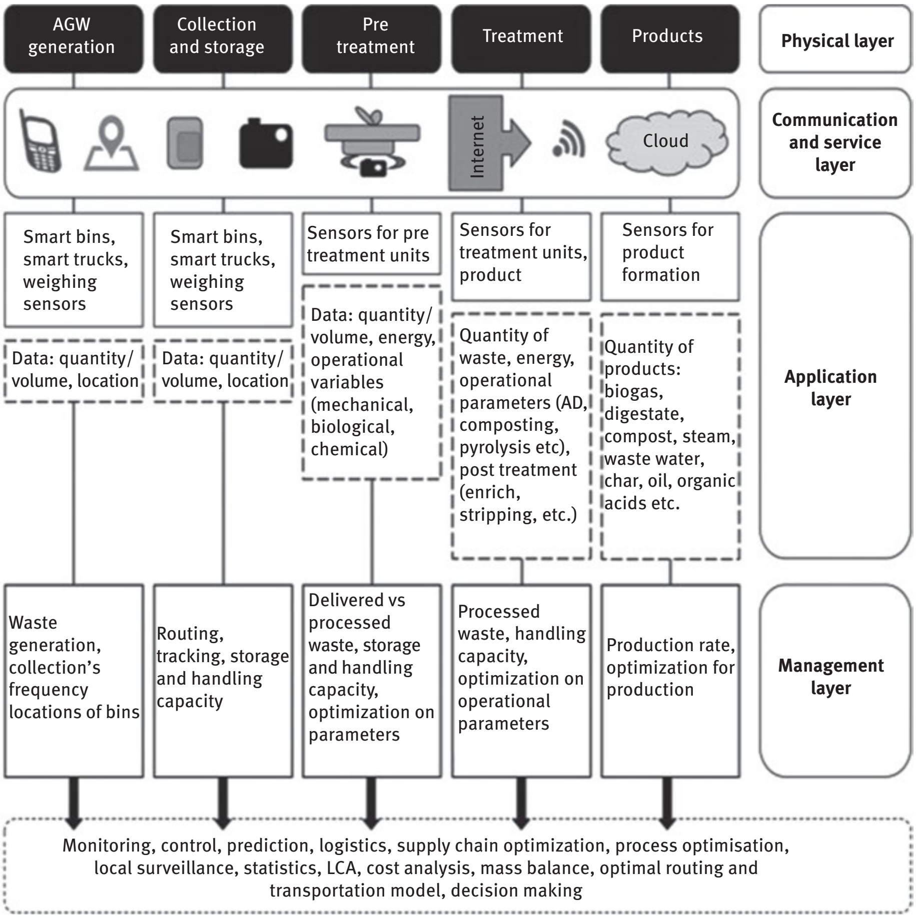

Figure 7.22: AWMS functions.
Source: (Research Gate/figure/Agricultural-Waste-Management-Functions) [41].

7.13 Conclusion

IoT-based smart farming is paving the way for Third Green Revolution. IoT in agriculture will bridge the gap between the production and yield quality and quantity. Smart farm with intelligent IoT operations improves the manufacturing process and makes the produce to reach the global markets faster. Every farmer has a goal to reduce the operational cost, increase the product value, and improve efficiency. These goals can be achievable and realistic with the help of IoT-based smart farming techniques. Farmers can make accurate and knowledgeable decisions to increase the output. This real-life espousal of an IoT solution will perfectly exemplify the expansion of global smart agriculture into remote areas and highlight the benefits that can be achieved using the latest technology.

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8 Internet of things platform for smart farming

Abstract: Internet of things (IoT) is referred to as a system of interconnected digital devices and software that function coordinately by sending and receiving data among themselves through a network. IoT can run various tasks without human–human or human–machine interaction. The tremendous possibilities that IoT carry have led to its implementation in agriculture. Statistics predict that in 2050, the world population will be over 9.6 billion. Traditional farming methods are inefficient in terms of usage of the resources for cultivation. Advanced farming techniques have to be implemented to feed such a vast population. IoT-enabled smart farming makes the efficient use of farmland and all the resources by using various sensors and other digital devices by which the farmers can get essential data regarding crops and various environmental factors. This will help farmers to cultivate crops by utilizing their resources in the best way. Different sensors and cameras can help observe the whole farmland with details such as temperature, moisture, humidity, and any possible threats that would harm the crops. This chapter discusses various tools and techniques for smart farming using IoT that will significantly increase the farming outcome.

Keywords: IoT, sensors, smart farming, cloud computing

8.1 Introduction

Around 58% of India's population has agriculture as the primary source of livelihood. In 2018–2019, our food grain production is estimated at 283.37 million tons [1]. Farm output of India is the second largest in the world. The efficiency of current agricultural methods has to be significantly increased to feed the growing population. In the year 2050, the world population is projected to reach around 9 billion. As indicated, United Nations' Food and Agriculture Organization, our food production has to rise by 60% to feed such a vast population [2]. Climate has a significant role in the growth and productivity of crops. The unpredictability of weather patterns can negatively affect the crops and, therefore, the farmers [3]. Climate change is expected to affect many countries, mainly tropical regions, severely. Changes in temperature and precipitation can impact crop production [4].

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https://doi.org/10.1515/9783110691276-008

The massive population is also a significant concern. The land resources for agricultural activities are declining dramatically. Since the start of the twenty-first century, 50 million hectares of land have been acquired throughout the world, and with the growing population, this number can never be expected to decrease [5]. Agriculture is also a significant threat to the environment. It has destroyed a vast amount of forest areas [6]. Destruction of forests and natural vegetation can cause serious harm to biodiversity and climate change. Throughout the centuries, the productivity of crops has significantly increased with technological advancements. The invention of synthetic fertilizers was a breakthrough in increasing food production [7]. The production of ammonia, which is an essential part of fertilizers by the Haber–Bosch process, was a breakthrough for the expansion of agriculture across the world [8].

On the other hand, excessive use of synthetic fertilizers is known to decrease the quality of soil and water dramatically. Studies have predicted that by 2050 most of the water resources in India will be under stress due to the increasing presence of nutrients in the water. The amount of nutrients is also directly proportional to the number of algae present in the water body, which in large quantities, can harm the water source [9].

Most of these problems arise due to the inefficient, traditional way of farming practices. If we incorporate modern farming technologies, the productivity of the crops and the farmlands can be significantly enhanced [10]. To limit environmental stress and forest depletion while ensuring food security worldwide is a complicated and challenging task. This is where smart farming comes into play by providing technological support to use land and other resources efficiently. Smart farming, with the extensive use of information technology (IT), is considered to be the fourth agricultural revolution [11]. The following sections of the chapter explore various technologies and devices that can be used to implement Internet of things (IoT)-enabled smart farming systems.

8.2 IoT-enabled smart farming

Developments in the IT field have produced sensors and other automated machines that can be incorporated in farming procedures. Precision farming is the use of such embedded sensors to collect relevant data depending on the site and crop to use it for farming processes. Precision farming is a significant step toward smart farming [12]. Maintaining productive farmland requires good knowledge regarding land and crops [13]. IoT is the key to implement smart farming, that is, by collecting relevant data from the farm by various sensors, processing it, and taking necessary actions based on site and crop with the help of various automated machinery [14]. IoT connects multiple electronic devices through Wi-Fi, Bluetooth, and radio-frequency identification (RFID). It also allows long-range connectivity using general packet radio services , 3G, and long-term evolution. IoT consists of devices that can be connected to a microcontroller and share and receive data through the Internet [15]. This helps farmers to access important information about crops, weather, and other essential factors that help manage and make farming-related decisions wisely [16]. With the current developments in information and communication technology (ICT), it is possible to monitor large farms by using a network of various sensors and other digital devices. Smart farming can also improve consumer acceptance of farm products. Use of ICT in farming optimizes the use of fertilizers, pesticides, and other resources. This improves the product quality and will be healthy for the society [11]. Use of IoT-based farming systems is becoming highly popular and is predicted to increase food production by 70% in 2050 [17].

IoT architecture consists of three layers: perception layer, network layer, and application layer. In IoT-based farming, the perception layer is generated by various sensors such as cameras, RFID tags and readers that collect the data from the soil and plants [18]. The network layer is how different devices are connected to send and receive data. Application level represents the applications that the abovementioned two layers perform. Applications include smart home and smart farm.

8.3 Communication technologies used in IoT

8.3.1 Radio-frequency identification

RFID is used in many applications such as supply chain management, transportation, and electronic antitheft systems. It has a lot of advantages in terms of communications that are the objects that do not require to be in line of sight to communicate. As communication is through radio waves, it can survive moisture, frost, and so on [28]. RFID system consists of three components. RFID is a great invention that can produce an IoT environment by enabling machines to identify objects, be aware of their conditions, and take actions if necessary [29]. RFID chips can be placed in plants to constantly monitor their health status. These chips can also be connected to smartphones or computers to visualize images and videos of plant conditions [30]. RFID communication is based on four different frequency ranges, low frequencies (LF, 30–300 kHz), high frequencies (HF, 3–30 MHz), ultrahigh frequencies (UHF, 300–3,000 MHz), and microwave (2–30 GHz). RFID readers and tags must be tuned to the same frequency to communicate with each other. With RFID sensors, the user can identify plant crops from weed and helps to eradicate weeds without affecting crop plants [31]. Table 8.1 provides a list of several wireless technologies used for smart farming.

Table 8.1: A list of wireless communication technologies to implement IoT.

Technology	Description	Range	Data rate	Reference
IEEE 802.15.4	They are designed explicitly to low-rate PAN. It consumes less power and low cost.	10 m	20–250 kbps	[19]
ZigBee	They are mostly preferred in low-rate data transmission and low power usage. It can transmit data over long distances by connecting to intermediate devices.	10–100 m	250 kbps	[20]
LoRa	A low-power wide-area network. Wideband linear frequency modulated pulses and its frequency changes based on the information encoded. It also has good tolerance to deviations in frequencies.	2–5 km in urban areas, 15 km in suburban areas	27 kbps	[21] [22]
6LoWPAN	The components of 6LoWPAN are connected by IPv6. It contains three elements: Host node – senses the environment and initiates the device, router node – intermediate nodes that take data from the host and send to the edge node, edge router – provides interconnection between 6LoWPAN and other networks.	10–30 m	250 kbps	[23] [24]
Bluetooth low energy	A low-power alternative to classical Bluetooth. Transfers data between devices in close proximity. Supports short data exchanges.	>100 m	2 Mbps	[25] [26]
SigFox	It allows billions of IoT devices to access the Internet. Network and processing are managed on the cloud. It consumes very less energy.	Internet connectivity	100 bps	[27]

8.3.2 Power line communication

Power line communication (PLC) enables the devices to communicate through the power systems they are connected to. Devices can transfer data through existing power lines, telephone cables, and so on. Compared to wireless communication, PLC does not create a load on the radio-frequency range. PLC also enables lots of devices to access a small amount of data by connecting to the same line [32]. PLC system can transfer date up to 1 Gbps. One main advantage of using a PLC system is that the installation process is easy and no additional work is required. PLC has several advantages over wireless communication technologies (WCT). WCT is good at monitoring large farmlands, but they are prone to obstacles. Wireless communication requires complex algorithms to transfer data within a network; this complexity can cause data loss while data transferring. This limitation can be overcome by using a PLC system [33].

8.4 Cloud computing technology for smart farming

Cloud computing facilitates the access of computing resources on demand by the user. This pay-as-you-go cloud computing model allows users who do not own data centers to access high computing power [34]. Cloud computing system consists of three different service models: the software as a service (Saas), the platform as a service (Paas), and the infrastructure as a service (Iaas). Iaas consists of the hardware layer that provides the computing resources. Paas consists of the operating system where the applications that are to be used can be executed. Saas is the software or program that runs on Paas/Iaas [35]. Several cloud-based smart farming services are available and a few of them are discussed next.

AgroDSS is a cloud-based service proposed by Kukar et al. [36] that aims to provide decision support for the user. This system uses data mining techniques to extract important information from a large library of data. Data mining systems, by using sophisticated algorithms, can efficiently identify important information that may not be visible to the naked eye. AgroDSS allows users to upload their data and analyze it with various data analysis methods and retrieve the output.

The team [37] proposed a cloud-based farm-as-a-service system which is designed to perform data collection, processing, and prediction of agricultural factors. This system is capable of identifying pests and plant diseases by analyzing disease and pest images.

8.5 IoT-implemented smart farming proposals

8.5.1 Smart farming robotic vehicle

Punjabi et al. [10] have proposed a remote-controlled vehicle that can do a wide verity of tasks such as sensing intruders, sensing soil moisture content, weeding, and applying pesticides. It can do smart irrigation by watering each plant according to its need, thereby conserving water from wastage. The system uses ARDUINO as its microcontroller and BC147 as its amplifier. The input data regarding soil moisture content is collected by the sensors and is transmitted to the microcontroller for the analysis. Based on the output data provided by the microcontroller irrigation is performed.

8.5.2 Smart farming system to detect borer insects in tomatoes

Rupanagudi et al. [38] developed a robotic car that can identify the presence of borer insect in tomatoes with built-in cameras and spray insecticides if necessary. The robotic system can move around the field and record the field processes. The processing of the recorded images is performed on a cloud server. An efficient video-processing algorithm was programmed using Java programming language for quick analysis of the recorded data. This algorithm quickly analyzes the uploaded data in the cloud and sent back the output to the robot to whether or not apply insecticide.

8.5.3 Automated irrigation and farm monitoring system

Vaishali et al. [39] implemented mobile smart irrigation management and monitoring system. This system uses Raspberry-Pi as its microcontroller; soil moisture sensors are implemented to detect the moisture content of the soil and temperature sensors to detect temperature. Sensors use copper electrodes to detect the moisture content. Blue Term, an android program, is used to send data to the main controller using Bluetooth.

8.6 Components of a smart farming system

8.6.1 Unmanned aerial vehicles

Unmanned aerial vehicles (UAVs) are remote-controlled aircraft that are used for monitoring farmlands. Unlike ground vehicles, UAVs can monitor a larger area and can provide data on each plant [40]. Unmanned aerial systems have great potential in smart farming. Many farmers are using such methods for monitoring, decision-making, weed management, and several other purposes [41]. These aircraft are capable of creating aerial images in RGB colors as well as infrared images. These images can provide valuable data on the condition of the plants because several color changes on the plants can be attributed to various diseases or activities of pests [42]. Therefore, UAV is a superior technology that can support efficient smart farming.

8.6.2 Soil moisture sensors

Irrigation is an essential aspect of agriculture, and the water should be used efficiently to get maximum benefits. Moisture sensors can calculate the moisture content of soil and can trigger the irrigation process once automated [43]. Such sensors are also developed as a part of solar-powered irrigation systems. The prices of solar-powered devices are decreasing. This technology can significantly save time and money for farmers [44]. Moisture sensors calculate the volumetric water content of the soil based on dielectric constant. The dielectric constant of the soil is directly proportional to the water content of the soil [45].

8.6.3 Soil pH sensors

pH is an essential factor for plant growth. Different plants require different pH mediums for their optimal growth and productivity [46]. Uncontrolled addition of fertilizers can also impact soil pH. If proper pH is not maintained, the nutrients will not be absorbed by the soil. Hence, monitoring soil pH is of great importance while considering good productivity of crops [47]. To date, different types of soil pH measuring devices are developed [48]. An on-the-go pH sensor can collect pH data while moving through the field. It consists of glass electrodes that act as electrochemical sensors to calculate the pH.

8.6.4 Weed detection

Applying herbicides uniformly across the whole field is a traditional practice that can reduce soil quality and crop productivity. Several automatic weed detection systems can discriminate crops from weeds and will allow the farmers to selectively apply herbicides on the weeds [49]. Weed detection systems mostly rely on computer vision techniques that work by color-based detection, texture-based detection, and shape-based detection of weed plants [50]. Burgos-Artizzu et al [51] have developed a real-time weed identification system from the captured video.

8.7 Conclusion

Developments in IoT have opened many opportunities to implement smart farming across the globe. Smart farming is the future of agriculture as it enhances a farmer's knowledge and ability to make decisions and perform by analyzing the conditions of various factors that affect the cultivation. Many countries have established smart farming systems that yield them good productivity. IoT connects a farmer's equipment with the Internet. It allows farmers to monitor his whole farm without physically being there. Smart farming, using of IoT, can revolutionize how the agriculture sector works now. Most of the jobs that are done by farmers will be handed over to machines that can perform much better, and humans will do higher-level tasks such as decision-making process and management. With the rapid growth of IT, the future of agriculture will be more connected to digital platforms and the Internet. This transition is inevitable to sustain the lives of dramatically increasing population.

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9 Internet of things platform for smart farming

Abstract: For thousands of years, agriculture is the center of our socioeconomic development. Even today, as much as approximately 2 billion people, that is, more than one-fourth of the world population, depend on agriculture for their livelihood. The agricultural production must increase by about 60% until 2050 to meet the growing population demand. While agriculture production must scale up significantly, the availability of key natural resources for agriculture like arable land, water, soil, and biodiversity are declining rapidly. Additionally, up to 40% of food crops are lost due to plant pests and diseases annually, causing $220 billion trade losses, and 30% of the food produced globally (approx. 1.3 billion tons), amounting to $ 1 trillion every year lost in the complex food supply chain. From the Neolithic Revolution in 10,000 BC, agriculture has seen four revolutions so far with the last one being the Green Revolution in the 1960s. Now, in the twenty-first century, agriculture is witnessing its next revolution through the Internet of things (IoT)-based smart farming. The widespread availability of the Internet connectivity and use of state-of-the-art technologies like smartphones, smart sensors, artificial intelligence, and IoT are transforming the agriculture industry every day. By optimizing utilization of resources and inputs such as land, water, fertilizer, and pesticides, it is not only making agriculture more financially viable but also reducing its ecological footprint. The proposed chapter aims at giving a detailed understanding of IoT-based smart farming ecosystem and each of its elements with real-world use cases and illustrations.

Keywords: Internet of things, smart, farming, precision farming, smart sensors, food supply chain, smart crop management, smart livestock management, smart logistics, machine learning, deep learning, artificial intelligence

9.1 History

Agriculture basically involves cultivating plants and livestock. For thousands of years, it is the center of our lifecycle. Agriculture was the most important factor in

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https://doi.org/10.1515/9783110691276-009

the rise of human civilization. The idea of farming domesticated species to create food surpluses enabled our ancestors to live in the cities. The history of agriculture goes as far as 11,500 years ago. Today, more than 3 billion people – almost half of the world's population – live in rural areas and almost 2.5 billion of these rural people derive their livelihoods from agriculture, says Food and Agriculture Organization of the United Nations (FAO) report [1]. This shows that till today it is a fundamental focus for our socioeconomical development. For many underdeveloped and developing countries, agriculture is the backbone of their economy. Between 1970 and 2017, global agriculture gross domestic product (GDP) rose from $0.9 to $3.0 trillion in real terms, contributing 3.9% to real-world GDP [2].

In 10,000 BC, the Neolithic Revolution is considered to be the first agriculture revolution, where people started experimenting with plants and learned about them. Humans adopted a lifestyle of hunting and agriculture for settlement, making large civilizations possible. It was followed by the Arab Agricultural Revolution (eighth–thirteenth centuries), British Agricultural Revolution (seventeenth–nineteenth centuries), and Scottish Agricultural Revolution (seventeenth–nineteenth centuries) during which many new crops were identified and technologies to support agriculture were developed and brought across the world.

Agriculture industry took one big leap during the 1950s and 1960s, with several technological types of research increasing agriculture production by improving agriculture output, that is, the Green Revolution or Third Agricultural Revolution [3]. After which, the world witnessed a massive 160% production increase in grain production between 1950 and 1984 [3]. As a result, average people in developing countries could consume roughly 25% more calories per day in comparison to earlier [3]. Post Green Revolution, farmers started to purchase inputs instead of generating them on a farm, which led to forming widespread rural credit institutes. This revolution brought approximately 15% increase in per capita GDP of developing countries during 1960–2000, as per the estimation from research conducted in 2018 [3].

9.2 Current situation and challenges

The agricultural production must increase by about 60% until 2050, according to the UN's estimates to meet the demand from increasing world population. From 7.6 billion in 2017, the total population is expected to grow to 8.6 billion by 2030 and 9.8 billion by 2050. Around 83 million people are born each year on this planet [4]. Approximately 26.7% of the world population, that is, more than 2 billion people depend on agriculture for their livelihood [5].

9.2.1 Availability of arable land and need to improve agriculture yield

While agriculture production must increase significantly to meet the growing population demand, the availability of arable land is declining. To add to the problem, by 2050, the available arable and productive land per person would reduce to 25% of the total that was available in 1960, as per the FAO report. This clearly means that agriculture yield must increase exponentially. While one farmer fed 4 people in 1900, the figure now is 155 people – and that figure is on the rise [6]. Additionally, majority of the world's farms are small or very small. About 72% of the farms are 1 hectare or less in size [7]. For example, as per Agricultural Census 2016 only 5% of farmers operate on land size larger than 4 hectares in India [8].

9.2.2 Availability of water and other natural resources

Agriculture sector is highly dependent on water. It is the largest user of water, accounting for 70% of use globally [9]. In recent years, due to global warming, many regions around the world are facing drought and going through extensive water shortage. In addition, surge in water demand from nonagriculture users, due to rapidly growing urbanization and industrialization, makes the situation more challenging for agriculture sector.

Not only water but also climate change is also reducing capacity of other natural resources like biodiversity and soil. The Intergovernmental Panel on Climate Change (IPCC) warns that climate change may cause diminutions of 10–25% in crop yield by 2050 [10]. Agriculture is not only the victim of climate change, and is also part of the problem at the same time. It contributes significantly to emission of 17% of greenhouse gasses (GHG) directly through agricultural activities and an additional 7–14% through land-use changes. It is therefore part of the problem and is potentially an important part of the solution [11].

9.2.3 Crop losses due to pests and diseases

Crop loss due to plant pests and diseases is one of the biggest challenges for agriculture sector. Up to 40% of food crops are lost due to plant pests and diseases annually causing $220 billion trade losses as per estimate from FAO [12], resulting in substantial economic deficit and raising food scarcity problem globally. Every year, farmers worldwide face the problem of significant agriculture yield loss due to crop pathogens and pests (P&Ps). In the 2019 NEE report, five major crops, making 50% of the global human calories intake, have suffered significant deficits due to P&Ps (10.1–28.1% in wheat, 24.6–40.9% in rice, 19.5–41.1% in maize, 8.1–21.0% in potato, and 11.0–32.4% in soybean) [13].

9.2.4 Food loss in supply chain

About 30% of the food production globally (approx. 1.3 billion tons) amounting to $ 1 trillion every year is lost in the complex food supply chain (FSC). It has a significant adverse impact on food security, economy, and environment. These losses vary depending on crop type, level of economic development, as well as social and cultural practices in a region. For example, as per the FAO report, these losses are highest during harvesting and sorting in fruits and vegetables. Losses during processing are significantly higher (14–21%) in developing and underdeveloped countries in comparison to (<2%) developed countries [14].

9.2.5 Livestock demand

Livestock management is very important as it is one of the key contributors in the agriculture sector. About 1.3 billion people worldwide earn their livelihood from it and it contributes about 40% to the global agriculture output [15]. By 2050, the projected global meat production is 465 million tons, which is double the 229 million tons in 1999/2001 and milk production is projected to 1,043 from 580 million tons as per the FAO report [15].

9.2.6 Price fluctuation and financial burden

Due to high price fluctuation for the agriculture output and influencing factors mentioned earlier, the farmers worldwide endure economical pressure pushing them to take higher debt, resulting in increasing interest burden on farmers' livelihood. In developing countries like India, where more than 70% of population depend directly or indirectly on agriculture, this burden has become one of the main reasons for farmers' suicide. Farmer suicides account for 11.2% of all suicides in India. Reports in 2017–2018 show that more than 10 farmers suicide per day [16]. As farmers continue to be under economic burden, investment in and adoption of new technologies is slow.

9.3 What is IoT-based smart farming

Research and application developments based on smartphones, sensors, machine learning (ML), deep learning (DL), Internet of things (IoT), and big data in various fields have unlocked many new possibilities and change the way how we see the world today. Enormous possibilities to collect the data and exploiting them for predictions and decision-making have opened up huge potential in every industry, be it automobile, healthcare, manufacturing, or services.

Smart farming, also known as farming 4.0, is the concept of using these modern state-of-the-art communication and information technologies to optimize each and every component of the agricultural value chain, as follows:

Optimal growth environment: With forecasting and real-time monitoring of the environmental factors to achieve the optimal growth for the plants.

Resources optimization: Monitoring the crops to provide what they want exactly – not more and not less, for example, exact amount of water, fertilizer, and pesticides.

Better understanding of the crops and livestock: Real-time field monitoring about growth of crops and livestock to understand their need at every stage of their lives.

Reduce the manpower dependency: Agriculture is one of the most labor-intensive fields, reducing this dependency through remote monitoring and controlling mobile applications and agriculture automation and robotics.

Boost quality and yield: Through field-specific weather and harvest time forecast, farmers can get higher quality harvest.

Save time and money: Reduce loss and waste at each stage of the supply chain, starting from crop selection until it reaches to the final consumer.

By integrating advanced technologies into the prevailing agriculture practices, smart farming is aiming to boost production quality and efficiency, and consequently improving the quality of life for the people directly or indirectly depending on it. By showing the real potential for providing productive and sustainable solutions, IoT-based smart farming has laid a strong foundation for the next green revolution.

9.4 IoT-based smart farming ecosystem

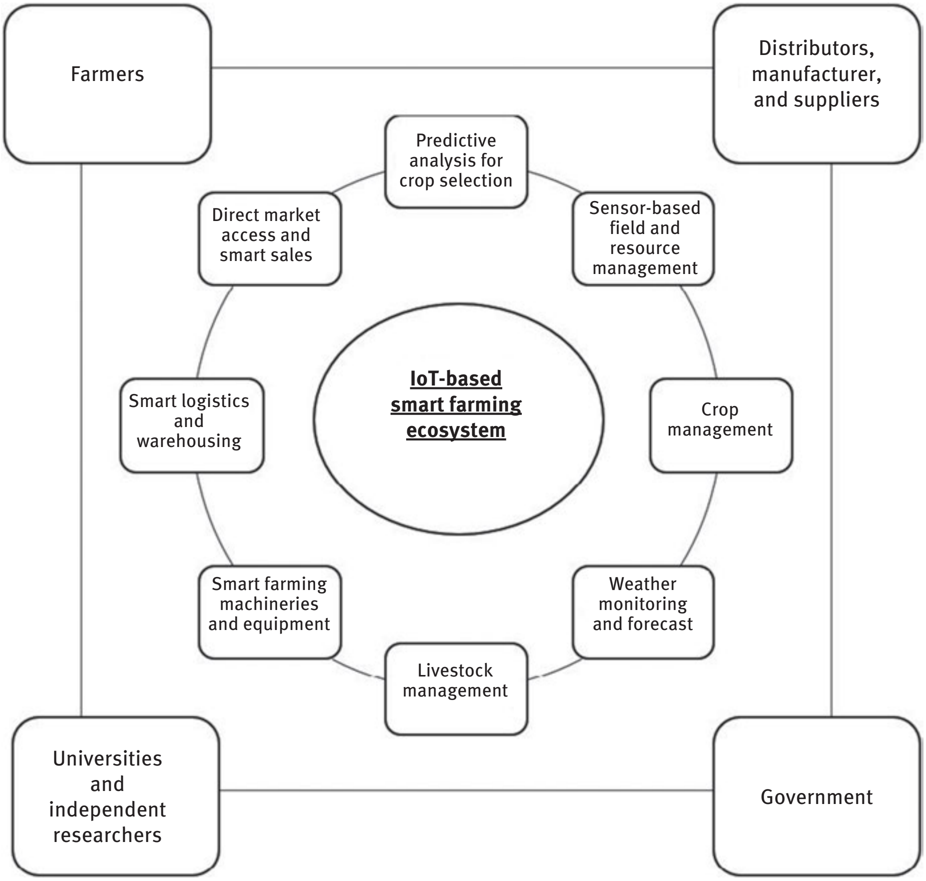

Figure 9.1: Model for IoT-based smart farming ecosystem.

9.4.1 Predictive analysis for crop selection

Demand for crop production is rising globally every day. Three major forces are:
1. Increasing human population
2. Meat and dairy consumption from growing affluence
3. Biofuel consumption

As per the study, by 2050, global agricultural production is required to scale up by 60–110% to meet these increasing demands as well as to provide food security to the ~870 million people who are currently chronically undernourished. Numerous researches suggest that rather than clearing more land for agriculture, boosting crop yields to meet these rising demands should be a preferred solution to meet this goal [17].

Amalgamation of ML and IoT has opened a new door for decision-making across many fields. Nowadays, in agriculture, the conventional farming methods are being replaced by precision farming by utilizing the combination of ML and IoT. To reduce crop loss and simultaneously increase the crop production, one of the most important components in farming cycle is crop selection. Deciding which crop should be grown depends on multiple factors such as climate, soil conditions, water, experience of farmer, labor availability, infrastructure, market demand, and government policies. Among these, weather and soil are the major deciding factors. This can be addressed by precision farming.

By gathering data through sensors and analyzing that data through ML algorithms, we can make personalized crop recommender systems for farmers. Modern IoT infrastructure can collect and transmit the data which can be used by ML systems to analyze patterns and find correlation of factors like weather, soil, and probability of disease.

Real-time data of soil moisture, temperature, humidity, and pH level can also be gathered by respective IoT sensors. These cost-effective sensors are usually controlled with a simple microcontroller. The sensors provide information on weather and nutrients in soil which helps to monitor the values and analyze the pattern in data by connecting to database. Arduino soil moisture sensor, LM35 temperature sensor, DHT22 humidity sensor, and pH meter are some of the widely used IoT sensors.

Using tools such as parallax microcontroller data acquisition add-on tool for Microsoft Excel, the information from sensors can be updated over Wi-Fi into the database. The data are then preprocessed and attributes are extracted before applying ML algorithms. The data set may contain attributes, also called features, like soil type, land type, temperature, humidity, pH, moisture, area size, rainfall probability, and a suggested class of crops.

Some of the popular ML algorithms for the same are support vector machine, decision trees, naïve Bayes, logistic regression, random forest, k-nearest neighbors, gradient boosting, XGBoost, artificial neural network (ANN), and DL.

As shown in Figure 9.2, the first step of crop selection process through IoT sensors the data is collected. Furthermore, user collected inputs such as area, soil type, land type can be added. The data are preprocessed and split into trained data set and test data set. Chosen ML algorithm is applied on trained data set and predictions are evaluated on test data set.

Based on the evaluation metrics such as mean squared error and accuracy, we can finalize an ML model for generating crop suggestions. The output is obtained by feeding the new values of all the attributes from farmer/user. As end result, we

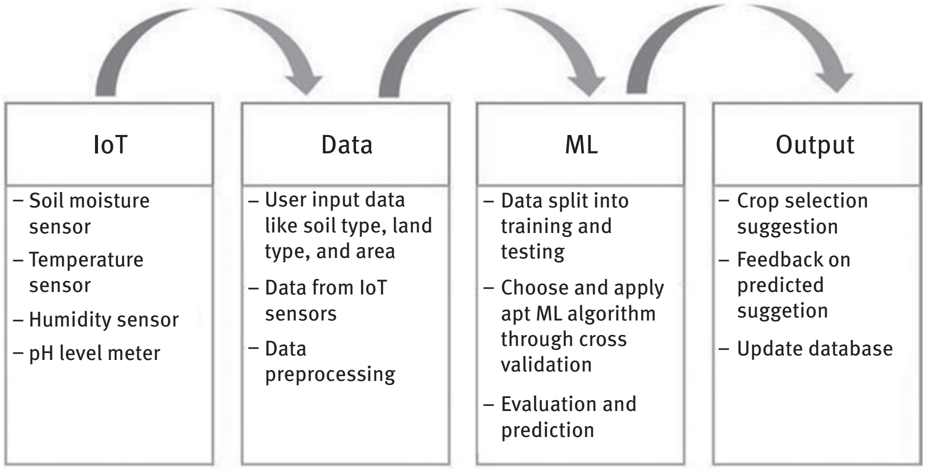

Figure 9.2: Generic crop selection process layout.

can recommend which crop should be grown. Additionally, we can develop a crop selection system enabling selection of fertilizer and predict the quantity of crop.

9.4.2 Sensor-based field and resource management

It includes two most important aspects of farming,
1. monitoring of soil condition and
2. precision irrigation,

Using smart sensor technology connected with IoT platform. Please refer to Figures 9.3 and 9.4 to understand the cycle.

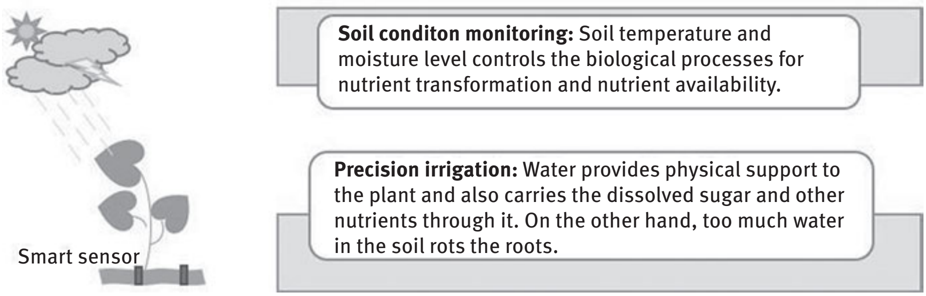

Figure 9.3: Areas of sensor-based field and resource management.

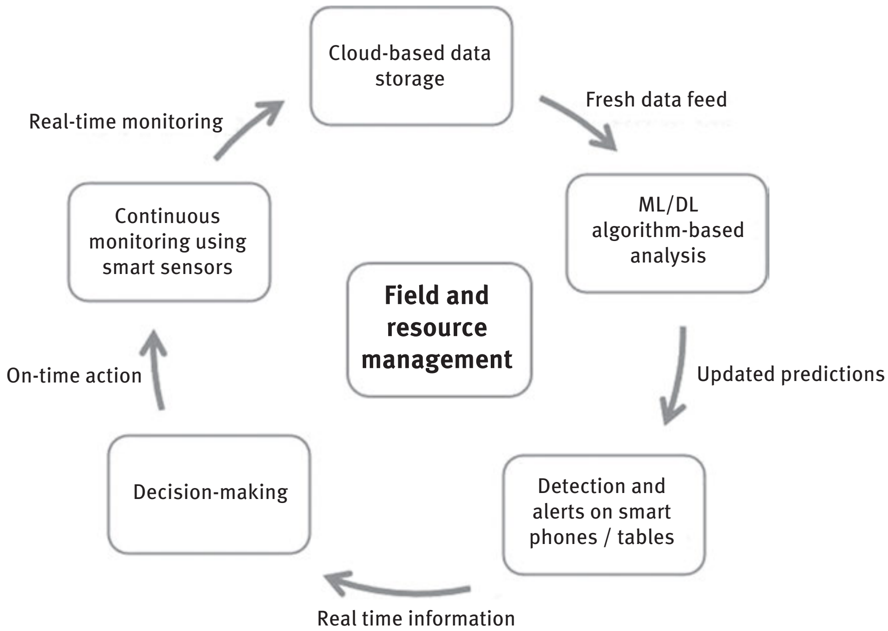

Figure 9.4: Model for IoT-based filed resource management.

9.4.2.1 Sensor-based soil condition monitoring

Use of soil condition monitoring sensors allow real-time data collection for the essential parameters like soil temperature, volumetric water content, rainfall, and supplementary metrics. Optimum soil temperature is vital for maximum growth and activity of soil microorganism. The soil temperature and the moisture level drive the biological processes for nutrient transformation and availability. This has direct influence on the factors responsible for crop growth like seed germination, root and shoot growth, and water and nutrient uptake. For example, if the soil temperature is above or below the particular range, the seeds do not germinate. Within 17–32 °C, microorganisms functioning in the soil are very active [18]. Based on the data provided by the soil condition monitoring sensors, soil temperature and moisture can be suitably controlled and adjusted.

The traditional way to check soil moisture is either by way of "feeling" it (which means by picking, squeezing, and observing a handful of soil) or sample test in the laboratory. First, guesswork is mainly based on experience, and second, it is time taking and costly. On the contrary, sensor-based IoT solution can provide real-time monitoring at affordable price.

9.4.2.2 Smart sensor-based soil monitoring solutions

9.4.2.2.1 Sensors for asparagus monitoring

Asparagus plants are highly temperature sensitive. For a plant to grow ideally, it requires day temperature between 23 and 29 °C and night temperature between 15 and 21 °C. Temperature outside this range would adversely affect the root and shoot development of the plants.

Additionally, high temperature can cause shoots to open prematurely, and at freezing temperatures, emerging shoots can become discolored, either event would result in poor quality yield [19]. As a solution to control the temperature, farmers use two-sided (black on one side and white on the other) sheet of foil.

To decide which side of the sheet to be kept in the direction of sunlight, farmers must monitor asparagus field temperature regularly. One smart solution is developed by the company Bosch. With the help of Bosch Asparagus App and deep-field temperature sensor, farmers can get the real-time temperature update on their smartphone and be relieved of manual monitoring [20].

9.4.2.3 Precision irrigation

Right quality and quantity of irrigation are very essential for healthy crop. Too much water in the soil spoils the roots, depriving the plant of absorbing the essential oxygen from the soil. Water also carries the dissolved sugar and other nutrients through the plant; so in dearth of the water, the plants will be malnourished.

Moreover, water also provides physical support to the plant. Not only quantity of the water but also its other properties like pH level, hardness, and temperature are equally important for the growth of a plant.

Every plant is unique and, accordingly, these factors can affect the growth of the plant. A real-time monitoring system can certainly help adjust them up to certain level to meet the plant's requirement optimally.

In general, water with pH level between 5.0 and 7.0 is considered suitable for irrigation. Water with pH level below 7.0 is termed as acidic and water with pH level above 7.0 is termed as basic. In acidic range, elements used by the plant for their growth are lesser and when it is in the alkaline side, water has lesser micronutrients such as iron and zinc. Certainly, there are some plants which can adjust to different pH levels and some even prefer or are required to have acidic soil [21].

If the water used for irrigation is hard, it contains larger amounts of both bicarbonates and salts. Such water forms layers of calcium and salt on the soil and the roots causing lesser water absorption. In combination with the fertilizer with high salt content, this will make it difficult for water to reach the roots. In terms of temperature, plants do not like rapid changes in the temperature since it induces stress and damage for them. Temperature change has direct effect on plant's germination, growth, and flowering [22].

Not only that, agriculture sector is also the largest user of water, accounts for 70% of water use globally [9]. In recent years, due to global warming, many regions around the world have been facing drought and going through extensive water shortage. In addition, increase in water demand from nonagriculture users due to rapidly growing urbanization and industrialization make the situation more challenging for agriculture sector, which makes precision water irrigation one of the most essential aspects of smart farming.

When real hydration level of the plants is not monitored, irrigation is merely guesswork.

9.4.2.3.1 Case of potato farmers in West Bengal, India

In the state of West Bengal in India, many farmers were contracted by PepsiCo to sell potatoes for PepsiCo wafers plant. Farmers saw high rejection rates for not meeting the quality standard set by the company. The rejected potatoes were greenish in color, high in water and sugar content.

One of the fundamental causes of such unaccepted quality was the improper irrigation. Such a problem can be easily solved using IoT-based soil moisture monitoring sensors, which can provide farmers real-time data regarding soil temperature and volumetric water content, and help them in taking informed decision regarding how much and when to supply water to the crop [23].

9.4.2.3.2 Smart sensor-based irrigation planning solutions

In the irrigation planning tool developed by Phytech (based in Israel), the sensors are attached to the plant's growing stem or fruit to continuously monitor microvariations in its diameter, which are scientifically proven stress indicators for the plants. The data are then updated in real time into cloud. Meaningful insights are delivered through algorithms, helping productive and plant-specific irrigation planning for farmers [24].

9.4.3 Crop management

Smart crop management includes smart farming applications in the area of sowing (seeding), crop diseases detection, fertilizers and pesticides management, weed control, and harvesting.

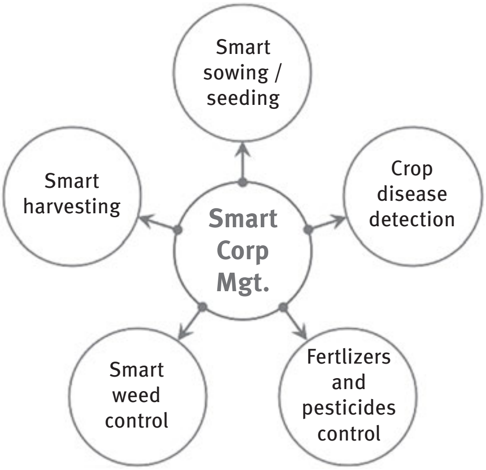

Figure 9.5: Areas of smart crop management.

9.4.3.1 Sowing/seeding

Followed by the land preparation, sowing is the process of placing seeds into the soil for germination; whereas harvesting, by definition, is the process of reaping and collecting the ready crop from the field.

Both the processes must be carried out impeccably for a good yield. Other than environmental factors, there are multiple parameters that can influence these processes.

For a successful sowing process, the seed size, the depth of sowing, and the row spacing are key parameters [25]. In harvesting, for grains, the examples of key parameters are – the moisture content of the crop, the ripe grains per panicle, the waiting time after sowing, and the heading as well as readiness for threshing. In the case of fruits and vegetable, determining points for harvesting are skin color, shape, size, aroma, in some cases opening of the fruit, change in leaf, firmness, abscission, content of juice, moisture, sugar, acidity, and starch [26].

During sowing, if seeds are placed too deep, it delays emergence and, in worst case, it may never see sunlight. Deep sowing also adversely affects plant vigor, that is, much of energy stored in the seed will be used in surfacing out [25, 27]. On the other hand, if the seeds are not placed deep enough, they may be washed away with the water from rain or irrigation or may serve as easy food bite for birds. Next parameter of focus is row spacing. While higher row spacing translates to underutilization of soil and lesser crop yield, it is again necessary for traveling, weed and stubble handling, soil throwing, and efficient use of preemergent herbicides [25, 27].

9.4.3.1.1 Intelligent planting solution

With the smart planting solutions, it is possible for the farmers to ensure that each of the abovementioned key parameters are managed precisely. In the intelligent planning solution from the company Bosch, based on the data collected by sensors, the system can automatically optimize the seed quantity for each row individually.

Also, such system provides control panel in the driver's cabin through which it is possible to control sowing parameters such as singulation, seed quantity, and displacement in real time. Problem of overlapping of seeding rows and uneven seed distribution during angular and curve paths can also be avoided through sensors used in such intelligent planting solution. Driver can monitor seeding process performance while working from inside the cabin. The system generates automated alerts in case of a problem [28].

9.4.3.2 Crop disease detection

Current methods for crop diseases detection like polymerase chain reaction, immunofluorescence, fluorescence in-situ hybridization, enzyme-linked immunosorbent assay, flow cytometry, and gas chromatography–mass spectrometry have limitations.

To name a few, they are laboratory-based methods requiring high-skilled analytics, complex sample preparation, and time taking, that is, no real-time detection in addition to high costs. If the diseases caused by the P&P's can be diagnosed timely and accurately, the losses can be minimized and completely avoided in best-case scenarios. Effective and efficient plant disease diagnosis would be a necessary step for state-of-the-art plant health management and ultimately for continued financial and natural growth of the world.

9.4.3.2.1 Smart crop disease detection

In recent years, the subfield of ML called DL is being employed by various industries to automate mundane tasks and solve complex problems. DL algorithms are based on ANNs, which are inspired by information distribution and processing of biological brain structure. Many of the modern DL models are built based on convolutional neural networks (CNNs), which is now a widely accepted technique for computer vision tasks such as image or object detection.

Start-ups like Agrix Tech (Cameroon) and Saillog (Israel) have developed mobile-based applications using smartphones to capture the plant images and DL algorithms to provide crop diseases detection [29, 30]. Such concepts can produce the best results with minimum investment for on-field plant disease detection.

9.4.3.3 Fertilizer and pesticide control

The ever-increasing demand requires fine-tuning each step of the production in agriculture. In the current section, the possibility of optimum utilization of fertilizers and pesticides would be discussed.

Soil loses its nutrients value over the period of time and if they are not replenished in time, its ability to support crop growth diminishes. Generally, farmers use fertilizers to supplement these lost soil nutrients. Pests are another bigger threat to plants, and to minimize their effect, farmers apply pesticides. There are organic fertilizers like livestock manure, slurry, and worm castings but they release nutrients slowly. So, to boost nutrients value quicker, farmers choose manufactured fertilizers. Similarly, there are organic pesticides too, but mostly chemical-based pesticides are preferred.

Since the beginning of the Green Revolution, the usage of chemical fertilizers and pesticides has been increasing rapidly every year. As per International Fertilizer Association survey on 88 countries, they consumed, on an average, 110 million tons of fertilizers per year between 1961 and 2010 [31, 32], out of which china used 21.6 million tons per year, the highest among all followed by the USA. In terms of pesticide, these countries used 342,000 tons of pesticide between 1990 and 2010. The USA used the most, that is, 90,000 tons followed by India [31, 32]. The growing use of chemical fertilizers and pesticides has left its impact.

Excessive use of chemical fertilizer and pesticides led to serious environmental problems like degradation of water quality, reduction in biodiversity and species composition, tropospheric smog and ozone production, as well as acidification of soils. In Europe and Australia alone, it resulted in loss of 42% species pool. In addition, because of different national policies, use of chemical-based fertilizers and pesticides is very uneven worldwide. This resulted in imbalanced nutrients values where Eastern Asian countries have surplus phosphorus, while most of the South American lands suffer from phosphorus scarcity. Similarly, nitrogen surpluses are common in most of the Asian countries and 80% of the African countries suffer from nitrogen deficiency [31].

Decreasing productive land and increasing futile pollution due to fertilizers and pesticides call for the smart solutions.

9.4.3.3.1 Smart fertilizers and pesticides management

This is one of the promising areas for future application development based on AI with only a few smart applications available for fertilizers and pesticides management. There are companies like SMART fertilizers management (USA) which provide a solution in which users feed the soil test data, and based on that, the company provides individual fertilizer management plan and schedule, considering the geographical and climatic consideration of the farm and soil analysis [33].

9.4.3.4 Weed control

Weed is generally defined as an unwanted plant or a plant that has grown at the wrong place. Because a plant that can be called weed in one context is not a weed when it grows where it is desirable. Weeds are very harmful to the crop growth because they compete with them for soil, water, nutrients, light, and space. They provide shelter to plant pathogens and serve as a medium for plant diseases. Moreover, they interfere during harvesting and contaminate the produce as well as release chemical substances that are harmful to the actual crop. Some special characteristics of weeds are the ability to reproducing aggressively, survive in adverse condition, and vegetative propagation structure – making them a major concern for the farmers [34].

Weed accounts for 5–10% agricultural losses in developed countries and the number in a developing country is more than 20% [34], since in developing country removal of weed is mostly done manually. Furthermore, weed has a considerable socioeconomical impact on farmers. As per a study on onion crop, depending upon the duration and intensity of the weed growth, the bulb yield loss can go up to 4% per day [35, 36].

At present, weeds are either removed manually or weed killers/herbicides are sprayed in the field. Either method is not efficient. Manual removal requires lot of labor, while an allover sprinkle of herbicide is not only wasteful but also hazardous to human health and environment [37].

9.4.3.4.1 Smart weed control system

A smart weed control system uses CNN, image processing, and IoT to differentiate weed from actual crop and identify the exact region – coordinates of the weed dense region. It is a targeted approach with precise measure of quantity of herbicide spray. Bosch has developed one such smart spraying system, which uses classic DL algorithms of computer vision to identify weed and once the weed is identified, the software of the system automatically selects the type of herbicide to be used and signal the sprayer on where to work. It takes 300 ms time limit for this system to recognize a weed and sprayer to spray [37–39]. Such systems can solve the weed problem efficiently and effectively.

9.4.3.5 Harvesting

Harvesting is one of the most costly and labor-intensive processes in the farming, accounting for almost 60% of the total cost per hectare [40]. Moreover, it has a strict time window – either early or late harvest may compromise the quality and quantity of the crop.

9.4.3.5.1 Smart harvesting planner

Readiness for threshing can be monitored in real time, and ideal harvesting time window can be calculated by observing key parameters.

For fruits or vegetables (the skin color, shape, size, aroma, opening of the fruit, change in leaf, firmness, abscission, content of juice, moisture, sugar, acidity, and starch) and grains (the moisture content of the crop, ripe grains per panicle, waiting time after sowing, and heading), sensor-based data points are collected.

If grains contain too high moisture, they are at risk of spoilage, and the too dry gains are subject to handling damage and they are more prone to insects in storage. Furthermore, dry grains lose weight as they shrink. Depending on type of grain, there is a certain waiting period in days after sowing and heading. Best time for harvesting grain is when 80–85% of grains are straw. There are charts and guidelines available from FAO and local governments describing right percentage of optimal pre- and postharvesting moisture content and waiting period [41] which can be used for building up a smart harvesting planner.

Many fruits and vegetables change their skin color when they ripen or mature – a clear indicator of the harvesting decision. Changes in shape, size, and leaf (e.g., optimum time to harvest in potatoes is after the leaves and stems have died), moisture content (e.g., moisture decreases and oil increases inside a maturing avocado) are good indicators, too [26]. Sensor-based real-time monitoring of these changes can be connected to a smartphone-based application through the IoT platform for the farmers.

9.4.3.5.2 Smart harvesting application (tomato-picking robot)

Harvesting is one of the most labor-intensive processes in farming, and concurrent declining labor availability makes it even more challenging. European Union (EU) estimates a 28% decline in agriculture workforce between 2017 and 2030 as per EU Agricultural Outlook December 2017 [42]. There are multiple companies and start-ups working on development of automated harvesting solutions.

One of such solutions for automated tomato pick-up is by Panasonic Corporation in January 2018. Harvesting tomato is a complex task, because each tomato must be pulled from the vine once it is ripe for harvesting, not before or later. Tomatoes are also very delicate and must be handled with care as single scratch in one piece can spoil whole box subsequently. Panasonic robotic system is fitted with high-resolution cameras, sensors, and AI platform, which can recognize and pick ready-to-harvest tomatoes and collect them in the basket. The company is confident that the initial version will have similar harvesting speed like humans [43, 44].

9.4.3.6 Other crop management solutions

Recently, the company Sony introduced a drone-mounted smart agriculture solution with real-time crop monitoring and management through image capturing and data analytics, which works without a network connection unlike many other Internet-based applications [45].

9.4.4 Weather monitoring and forecast

Many of us check the weather forecast for the day each morning to plan our day. The criticality of the exact forecast can never be overstated for farmers. The weather conditions command the crop growth, total yield, water, and fertilizers requisite in addition to the occurrence of pest and disease.

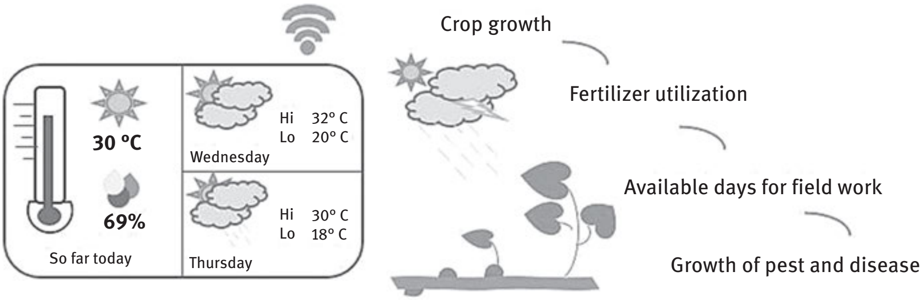

Figure 9.6: Decision-making through weather monitoring and forecast.

Crop growth: The appropriate amount of temperature, light, and moisture is the deciding factor for crop growth. Availability of accurate real-time and historical data about it can be very helpful to farmers in monitoring the growth of the crops and taking informed decisions such as when and how much to irrigate, when to protect plants from sudden change in the temperature and frost, as well as when to plant and harvest. All these decisions have direct impact on farmers' financial balance sheets.

Application of fertilizers: Timing and quantity of fertilizers are two major decisions for farmers, which are heavily influenced by weather. If not done right, it can wipe away complete yield. The weather must be dry enough so that fertilizer does not wash away; on the other hand, soil must be moist enough for fertilizers to work effectively.

Pests and disease control: Particular weather conditions boost the development and progress of the pests and diseases. Real-time weather monitoring can be very useful in order to decide if and when to apply pest and/or disease controls. Forecast and monitoring of wind speed also play an important role, where farmers are using drone or crop dusters/aircraft for applying pest and disease control. If wind conditions are not favorable, there is a high risk of missing the targets.

Available days for field work: Availability of suitable days for farming or field workability is primarily depending on soil temperature and moisture. Reliable weather forecast and monitoring can be very helpful for farmers in planning day-to-day activities and farming season.

9.4.4.1 Smart weather monitoring platform

IoT-based weather monitoring solutions from Sigfox and Bosch are a couple of such examples.

Sigfox IoT-based platform can monitor rainfall, temperature, wind speed and direction, air pressure, and humidity, and help farmers to take informed decision regarding crop management [46].

Bosch ProSyst IoT platform has developed a smart solution for oyster farmers. Oyster farming is very challenging as they can absorb contamination from their surrounding very quickly, which is harmful to humans. Due to this, in most of the countries, farming of oysters is highly controlled.

False alarm from authority to suspend harvesting temporarily due to threat of high contaminations can cost huge loss to farmers. Rainfall reports are normally the basis for such decisions of suspending farming temporarily, as rainwater also brings contaminations with it. Bosch ProSyst IoT platform measures depth and salinity of the water, as well as atmospheric pressure and temperature, through monitoring stations in area where oysters grow, and the algorithm developed by the company provides accurate information to farmers on their smartphones if it is right time to harvest or not. As a result, it is now possible to reduce unnecessary closures by almost 30% [47].

Another such sensitive plant is strawberry. It can be victim of subzero temperatures at night. Especially when plants are beginning to flower, growers have to protect them by covering them from subzero temperature. In absence of protection, they might freeze and farmers can lose complete yield. The risk is particularly at night, for subzero temperatures, during strawberry farming season.

In the absence of any smart app, farmers must keep watch during night in order to protect their crops. Deepfield Robotics, a Bosch start-up has developed such an application, that can monitor the strawberry crop and inform farmers on their smartphone when the plants need to be protected.

9.4.5 Livestock management

In 2013, livestock accounted for one-third of global agriculture gross production as per FAO report [49]. As much as 1.3 billion people across the globe are depending on it for their livelihoods. Inarguably, it is a fundamental contributor to global human calorie intake [49]. Milk, meat, and eggs provide 16% of total calories and 31% of dietary protein as per FAO 2010 report [49]. Animal products are source of essential micronutrients such as iron, vitamin A, iodine, and zinc. For farmers, livestock serves them in different ways, be it source of income and employment, food and social security, or means of draft and dung. As the largest exporters, the livestock products are pillars for economies of countries like Australia, New Zealand, the EU, the USA, and Brazil. India, with the largest livestock inventory in the world, is the world's largest milk producer and beef volume supplier. Livestock sector contributes 4.11% in the GDP and 25.6% of total agriculture GDP of India [50]. For sub-Saharan and South Asian countries, livestock contributes even higher, up to 40%, agriculture GDP [51].

By 2050, projected global meat production is 465 million tons, which is double the 229 million tons in 1999/2001 and milk production is projected to 1,043 from 580 million tons as per FAO report [15]. To meet these future targets with increasing demand fueled by population growth, the livestock production must be optimized.

Moreover, it must be noted that, almost one-third of global arable land and 8% of fresh water is consumed by livestock production cycle [52]. It contributes as high as 14.5% of global anthropogenic GHG emissions [53] and is largely responsible for deforestation and biodiversity loss [52]. Hence, the resource utilization must be balanced with more output, lesser waste and pollution possibilities.

Looking at the current livestock management scenario, a constant challenge for the farmers is high-impact animal diseases, especially in the developing countries where capacity to control such diseases is limited. Diseases such as foot-and-mouth disease, highly pathogenic avian influenza, classical and African swine fever, trypanosomosis, and Peste des petits ruminants are endemic in some of the world's high livestock producing countries in Africa, Asia, or Latin America [54].

Additionally, lower meat and dairy price, volatile demand patterns, demand for "always fresh," increasing consumer demand for transparency about animal health, welfare and living conditions, as well as changing rules for use of antibiotics are calling for the use of smart technologies for optimal livestock management.

9.4.5.1 Smart livestock management

Smart livestock management uses state-of-the-art technologies like camera, sensors, microphones, smartphones, and drones in order to monitor the status of the livestock continuously and automatically. It supports farmers in everyday activities like animal feeding, health and welfare monitoring, location tracking, waste management, as well as staying informed about global best practices and market trends, thus making operations more efficient and effective.

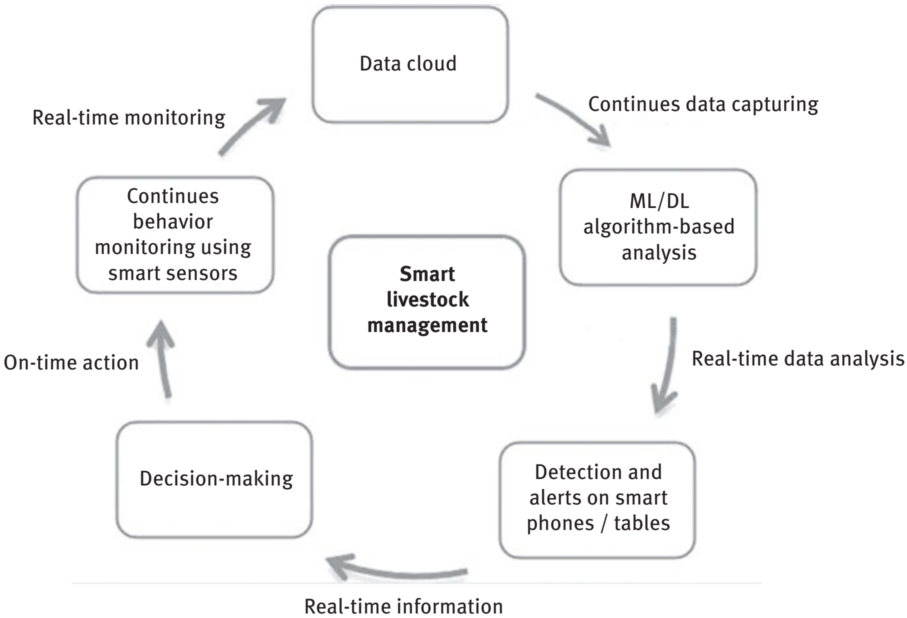

Figure 9.7: Smart livestock management.

Such platforms automatically collect and analyze animal data such as physiological parameters, production measures, and behavioral traits. This can provide valuable inputs to farmers for major decision-making, enabling early health, and well-being diagnosis in individual animal and hence the application of appropriate corrective husbandry practices. With this, animals can receive best care with minimal waste and production cycles are fine-tuned.

9.4.5.1.1 FAO platforms

FAO has developed quite useful platforms like laboratory mapping tool (LMT), EMPRES-i, and surveillance evaluation tool (SET) to support smart livestock management.

LMT: A scoring system developed by FAO for veterinary laboratories aiming to strengthen laboratory capacity for early detection and diagnosis of diseases, enabling rapid response to emerging issue [55].

EMPRES-i: A global animal diseases information system designed by FAO's Emergency Prevention System. It is a web-based platform that provides real-time information on animal disease distribution and current threats at national, regional, and global levels [56].

SET: A toolkit, which provides a systematic way to evaluate countries' capacities to detect and report animal disease. It uses 90 different indicators to score a system like policies, laboratory capacity, data management, field capabilities, and more [57].

9.4.5.1.2 Smart livestock management solutions

Smart livestock management system monitors the animal behaviors through camera and sensors during normal daily activities like feeding, drinking, ruminating, moving, standing, and lying. It analyzes minor behavior changes using AI and ML/DL algorithms to provide early alerts and decision-making assistant regarding important aspect of livestock management like disease, mastitis, calving, heat, and dysstasia. One such platform was developed by a Japanese start-up Desamis called U-monitor. Technology uses three different types of sensor (3D-acceleration, pneumatic, and proximity sensor) fitted in the neck tag of the animal [58].

The birthrate of cattle is another key target to meet the ever-increasing demand for animal products. To make breeding efficient, it is important to monitor a cow to detect when she enters estrus and then inseminating at the right time. Though the challenge is in, 60% occurrences, the cow that enters estrus stage at night, when this is missed at the first time, the farmer is forced to wait for another 3 weeks. So, without a round-the-clock monitoring, it is difficult to detect the behavioral signs of upcoming estrus stage. In many cases, fertilizing a cow via artificial insemination requires two or more attempts. Japanese company Fujitsu Kyushu Systems Limited has developed a smart solution using pedometer. A sign of entering estrus is a substantial increase in walking. By attaching pedometer to the cow's leg, it is possible to count the number of steps taken within 24 h. The application accurately predicts when estrus could start and notify the farmers on their phones. As per the company report, by using this application, farmers can achieve successful fertilization in a single artificial insemination attempt in up to 90% cases [59].

9.4.6 Smart farming machineries and equipment

The farmers need methods to surpass their current productivity massively in efficient and sustainable way to meet the demand of 9.8 billion people in 2050.

Smart equipment and machineries connected through IoT platform can be one big leap. Following are the technologies used for smart farming equipment and machineries [60]:

High-precision positioning systems (like GPS and Galileo): These are navigation technologies which can provide reliably accurate positioning while driving on field.

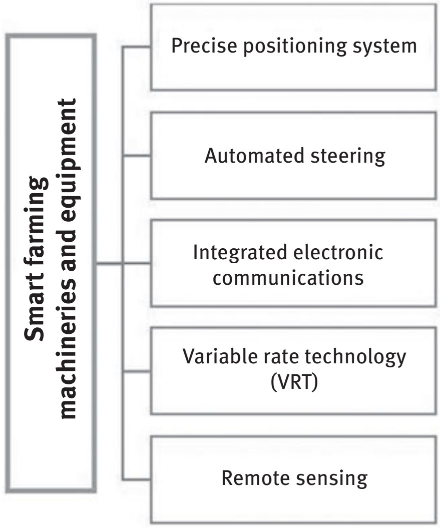

Figure 9.8: Technologies used in smart farming equipment and machineries.

Automated steering system: It can assist the farmers and even take self-control for tasks like autosteering, overhead turning, following field edges, and overlapping of rows. By reducing the human error, these technologies can be very effective in site management.
Integrated electronic communications: A technology enabling communication between various equipment and machineries, between tractor and manure spreader or monitoring drown and sprayer.
Variable rate technology: This makes farming equipment and machineries to adapt parameters as per actual variation in plant growth or soil conditions.
Remote sensing: With the use of different sensors equipment and machineries, it can collect data regarding soil conditions, environmental conditions, crop health, and so on.

Many solutions arrive every day in the market in the field of smart farming equipment and machineries. About 70–80% of new farm equipment sold in Europe offer precision farming (PA) technology concept, as per machine industry data [61]. Smart solutions have applications not only in various processes of farming, starting from soil preparation until harvesting [62–64], they also provide solutions for smart preventive maintenance [64] and fleet management [65] of farming equipment and machineries.

9.4.7 Smart logistics and warehouse

9.4.7.1 Postharvest losses

Postharvest losses (PHL) is a major reason of food loss. Quantitative and qualitative losses of food during various postharvesting operations are referred to as PHL, costing 30% of total produce while affecting food security, economy, and environment. These losses vary depending on crop type, level of economic development, as well as social and cultural practices in a region. In industrialized countries, losses amount to approximatetly $680 billion, and in developing countries around $310 billion [66]. Compared to rest of the food groups, the global quantitative food losses and wastes are highest in the fruits, vegetable, and roots crops; that is, ca. 40–50%. For cereals, it is 30%; for oilseeds, meat, and dairy products, it is around 20%; and 35% for fish [66]. Not less than 50–60% of the cereal yields are lost at the storage in absence of proper harvesting and storage techniques [66]. In terms of losses during the processing, they are significantly higher (14–21%) in the developing and underdeveloped countries in comparison to <2% in developed countries [14].

PHL can happen due to variety of causes. Broadly, it can be categorized in the following segments [67]:

Agricultural production: For the vegetable commodities like fruits, vegetables, and root crops, agriculture production losses refer to losses due to mechanical damage or spillage during harvesting process; for animal commodities like bovine, pork, and fish, it refers to animal death during breeding; and for the milk, it is the decreased milk production due to dairy cow sickness.

Postharvest handling and storage: Death of animals or spillage and degradation of vegetable commodities and milk during handling, storage, and transportation between farm and distribution is considered as postharvesting handling and storage loss.

Processing: It includes losses during domestic or industrial processing of vegetable and animal commodities. For example, losses during juice production and backing, losses due to trimming spillage during slaughtering, or losses during treatment of milk.

Distribution: Losses at various distribution channels like wholesale markets, supermarkets, and retailers are categorized under distribution losses.

Consumption: Waste or losses at household are referred to as consumption losses.

Reducing PHL is essential for reducing world hunger, poverty, and burden on natural resources.

9.4.7.2 IoT-based smart logistic and warehousing solutions

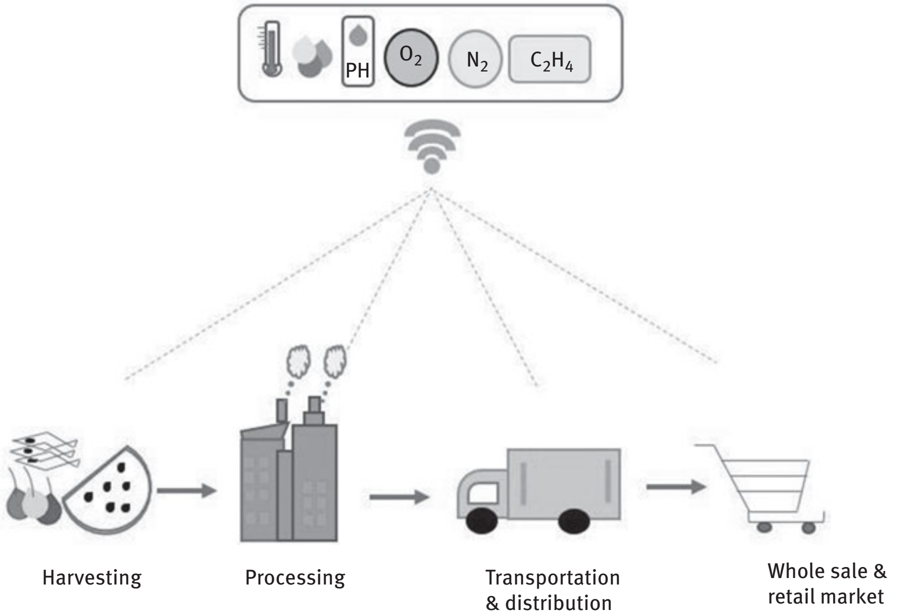

Figure 9.9: Monitoring of food shelf life throughout FSC with IoT platform.

Real-time monitoring of food through continuous data collection using sensors throughout the FSC is a significant step forward in order to reduce PHL. Food traceability though sensor-based IoT platforms can reduce food waste between 5% and 7% as per new World Economic Forum report [68].

Usability of the food product is determined by its shelf life. It is the time period for which the food product remains safe and fit for use. Shelf life of the food mainly depends on two factors:

1. Microbial growth (which leads to the spoilage of the food) and
2. The growth of microbial pathogens that affect the food safety [67].

Various factors like water activity (aW), pH value, relative humidity, storage temperature, and ambiance (level of oxygen, nitrogen, and ethylene content in the air around the product) can be used to monitor them [67]. IoT-based smart logistic and warehousing platforms can provide accurate information for current condition of the food and provide reliable forecast for remaining shelf life for logistic decisions.

9.4.7.2.1 Smart logistic and warehousing solutions

One example of such smart logistic and warehousing platform is IBM Food Trust. It is a block chain-based FSC management system that provides access of actionable FSC data to authorized users throughout the FSC [69].

Milk monitoring system developed by Bosch Deepfield is another example for smart logistic solution, using infrared sensors to gather data on real-time condition of the milk throughout its journey. The milk producers receive analyzed reports on product status though Bosch IoT cloud in their smart phone [70].

9.4.8 Direct market access and smart sales

Due to high price fluctuation in the agriculture output, growers worldwide face economic pressure pushing them into higher debt, resulting into increasing interest burden on farmers' livelihood. About 2.4 million farmers left the business between 2005 and 2010 in EU due to price volatility and change in structural characteristics of the market, as per FAO [71]. High level of debt and increasing interest rates weigh on farmers' livelihoods.

In India, where more than 70% people depend directly or indirectly on agriculture, it has become one of the main reasons for farmers ending their lives. Farmer suicides account for 11.2% of total suicides in India. For agriculture products, market fluctuations in the prices are common, but they have highly negative impact when they are dramatically volatile and unexpected. For example, volatility of onion price in India. In 2019, it went up from 656 INR/kg in January 2019 to 5,750 INR/kg in December 2019, which is a spike of more than 750% [72]. Still economic and social conditions of the farmers remained unimproved, clearly indicating toward the need for a transparent and efficient distribution system for the agricultural product.

9.4.8.1 Direct market access and smart sales

IoT-based smarts platforms can directly connect farmers to the end consumers thereby shortening the supply chain and yields direct benefit of price change for farmers. Moreover, projection of market demand using predictive analysis models trained on ML and DL algorithms can provide farmers with reliable forecast regarding market demand and using smart farming tools farmers can accurately forecast their yield, helping them to balance demand and supply. Direct market access and smart sales platform has following advantages:

1. Elimination of nonvalue-added activities in farming supply chain
2. Direct access of the market to the farmers

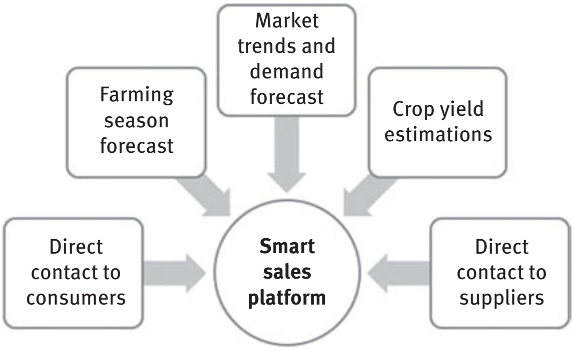

Figure 9.10: Elements of a smart sales platform.

3. More transparency in supply chain
4. Demand and supply balance through ML- and DL-based predictive analysis tools
5. Up-to-date market information and early adoption to the changes
6. More power to the farmers

9.4.8.1.1 Smart solution

As an initiative from Indian conglomerate Indian Tobacco Corporation Limited, e-Chopal platform is an example of smart sales platform, which connects the farmers directly to the company by eliminating the middlemen in the supply chain. This portal also provides the growers with weather prediction, market prices, information on farming, best practices and risk management, as well as facilitates the purchase of farm inputs, which helps farmers in informed decision-making and earning direct benefits [73].

Even though there are many successful cases of smart sales platforms in retail business, this area of smart farming is not much explored yet. It can be a key element for the success of IoT-based smart farming ecosystem.

9.5 Future scope

Although technology is penetrating one of the oldest industries, agriculture, there is a lot of untapped potential for technological revolution in this field. Innovation has not been able to match the pace of increasing food scarcity and hunger. Rapid urbanization is changing demography with young people migrating to cities. This has resulted in shrinking of rural population which is responsible for majority of farming activities. Moreover, to industrialization, we have lost significant amount of arable lands. Conventional agricultural methods have been also responsible for approximately 80% of deforestation.

Farming is known to be an outdoor operation. Sunlight, soil, water, and nutrients are the essential resources for plantation. Over the time, farmers have tried their hands at indoor farming. This way of farming has noteworthy benefits such as some crops can be produced all year long irrespective of the weather conditions and there is no need for pesticides. Greenhouse-like method do speed up the growth of plants and procures higher crop yield than outdoor farming. European farmers began using greenhouse process in the 1800s to grow plants for which they did not have suitable natural surroundings. This methodology of indoor farming is certainly able to push the limits faced with outdoor farming, but it still requires large space or area.

Vertical farming is a fairly new technology to grow vegetables and various plants on vertically stacked layers all year round. Unlike greenhouse, in this method, structures like a tall building, shipping container, or unused warehouse in cities are utilized for farming. The chief objective of vertical farming is maximizing crops output in as minimum as possible area. Vertical farming incorporates technology-based approach called controlled environment agriculture (CEA) in which factors like temperature, light, humidity, gases, and nutrients are artificially controlled to attain optimal growing conditions. Hydroponics, aquaponics, and aeroponics are soilless farming CEA techniques.

In hydroponics, which is a subset of hydroculture, the roots of the plants are submerged in water solvent with mineral nutrient solutions. To ensure the maintenance of the correct chemical composition in the nutrient solution, they are constantly monitored and circulated. The Space10 innovation lab of IKEA uses this method in their prototype project named Lokal. As per their claim, hydroponics enable them to grow greens three times faster than in a field, using 90% less water, without needing soil or sunlight, requiring much less space than traditional farming and producing much less waste. Tomatoes, peppers, cucumbers, lettuces, and marijuana are few of the commonly grown plants with hydroponics.

An aquaponics system is a kind of extension to the hydroponics system. It aims to combine the aquaculture and plants in the symbiotic ecosystem. In this system, fishes grow in indoor ponds and their excretions are subsequently broken down into nitrates, which act as a nutrient-rich source for the plants being grown in vertical farms. The wastewater gets recycled and directed back to the fishponds. Currently, aquaponics is used at a smaller scale than most vertical farming techniques. In future, there is a scope for implementation of scaled-up standardized aquaponic systems. Salad plants are well suited to be grown with aquaponic systems.

In the 1990s, National Aeronautical and Space Administration was looking for a sustainable technique to grow plants in space. This technique motivated the innovation of aeroponics. Aeroponics is the process of growing plants in an air or mist environment with no soil and very little water. Aeroponics is still an anomaly technique in the world of vertical farming techniques, even though it has started getting attention.

One of the primary advantages of vertical farming is its higher yield compared to traditional farming. In some cases, vertical farming produces over 10 times the crop yield per acre than traditional methods [74]. This method of farming controls the input of plant-fertilizing nutrients which results in highly nutritious food. Indoor vertical farms are less likely to feel the brunt of the unfavorable weather, providing greater certainty of harvest output throughout the year. Another major advantage of vertical farms is centralized distribution. These farms can be built easily in urban premises, which makes them nearer to local customer base. This saves lot of transportation costs and reduces remarkable amount of emission. Moreover, vertical faming would make environmental conservation possible by avoiding deforestation and desertification caused by agricultural encroachments.

Vertical farming has still to overcome the economic challenge while the profitability of vertical farms is still debated. The cost of buildings for farming added with other costs such as lighting, heating and labor may outweigh the advantages. However, with use of renewable energy, recycling of resources, usage of energy efficient LEDs, such as blue and red shades of lights, rainwater harvesting the vertical farms can be made more economy viable. Furthermore, the challenge of high cost of building facility for farming can be resolved by using shipping containers and former factories or old warehouses.

Vertical farming technologies are still relatively new. The performance of companies like AeroFarms, which is the commercial leaders in this field with their innovation of using the aeroponic system of farming, will determine how important a role vertical farming will play in the future to face the challenge of growing food demand.

Desserts and ocean cover the majority of surface on the Earth. Turning world’s desert and ocean into food production facilities can be an alternative to tackle the ever-increasing food crisis. To reduce plastic pollution, biodegradable food packaging is a need of an hour. Research in this direction would allow us to build sustainable world for upcoming generation.

Lastly, new technologies such as gene editing, lab-grown meat, and three-dimensional printing are also creating entirely new kinds of foods.

The research in all the directions discussed here offers great promise to make it ready to meet the scaling future demand through leveraging out-of-the-box approaches.

9.6 Conclusion

From the Neolithic Revolution in 10,000 BC, agriculture has seen four revolutions so far with the last one being the Green Revolution in the 1960s. Now in the twenty-first century, agriculture is witnessing its next revolution through smart farming. Widespread availability of the Internet connectivity and use of state-of-the-art technologies like smart phones, smart sensors, AI, and IoT are transforming the agriculture industry every day. Using these technologies, it is possible to continuously collect the real-time data through entire agricultural supply chain and convert them into insightful information and predictions. It is a much-needed empowerment of farmers and other stakeholders to take well-informed decisions and actions. Smart farming is making agriculture more efficient. By optimizing utilization of resources and inputs such as land, water, fertilizer, and pesticides, it is not only making agriculture more financially viable while reducing its ecological footprint. A well-integrated robust IoT-based smart farming ecosystem is certainly the definitive solution to ever-increasing world's food scarcity in a profitable and sustainable way.

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Part III: **Applications of machine learning in agriculture**

Suvarna Pawar and Pravin Futane

10 Kisan-e-Mitra: a tool for soil quality analyzer and recommender system

Abstract: Agronomics is a major concern for agro-based survival nowadays. The proposed expert framework is likely to assist ranchers to improve their efficiency and sustainability. The major concern is to remotely monitor the quality of soil in real time, by getting live sensor data, and recommend the nutrients that need to be added to improve the soil quality. To contribute to the agriculture domain, gadget gathers information on the basis of field soil quality monitoring and measuring system. The soil sample is collected from the field and tested at the Kisan-e-Mitra to analyze the quality of the soil. This process calculates nutrients that are available in the soil. The tool is created for the purpose of soil analysis and recommendation that can be easily made available to the farmers to have maximum yield. This idea is unique since it replaces the traditional lab testing approach for soil quality analysis and recommendation, which turns out to be more costly, time-consuming, as well as laborious. Instead of the traditional approach, a group of farmers can purchase a single soil quality analyzer and recommender tool kit and facilitate agricultural productivity more efficiently and conveniently.

Keywords: Internet of things, Kisan-e-Mitra, agriculture, cloud computing, sensors

10.1 Introduction

The agricultural sector is the dominant playback for most farmers in India as it gives their bread and butter. Crop development carries a major role in economics and is the reason for survival of people in India. This tool makes the soil quality analysis easily available at one’s doorstep, which may save their valuable time of lab testing. The aim of this chapter is to propose a smart soil quality monitoring using Internet of things (IoT) and machine learning-based system that can assist farmers in crop management by getting live updates of different attributes related to soil for increasing productivity of the farm yield. This enables smart farming and increases their overall yield and quality of the products. Many of the industries have transformed themselves to the IoT technologies and agriculture is also one of the sectors. This will not only detect the micronutrients value for real but also

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https://doi.org/10.1515/9783110691276-010

advise farmers about feeder for soil area. According to the generated live data from the microcontroller and IoT kit, recommender system (feeder) will feed the natural composites to the farm to fill up the gap of micronutrients. Nowadays many of the farmers are using the chemical compounds to gain the look and texture to the product they are willing to produce. This natural composite (Sendriya Sheti) is replacement to the chemical compounds, which may save many of the lives by reducing the death ratio due to cancer and other severe diseases. Organic farming (Sendriya Sheti) is an alternative agricultural system that originated early in the twentieth century in reaction to rapidly changing farming practices.

Recent surveys mention that there is no existence of any doorstep device for the farmers where soil analysis and testing is done. It can analyze the soil quality texture using IoT kit and draw the lagging contents, that is, micronutrients of soil. It also suggests and recommends the natural composites to fulfill the requirement of the soil and achieve gain in nutrients value. As an innovation on organic farming, The amount of composites added to this device.

10.2 Literature survey

Muhammad Shoaib Farooqet et al. [1] have beautifully mentioned the today's scenario of agriculture in terms of the technological aspect. It has represented the current scenario of how IoT has been used widely with the current use of sensors and all other related tiny operating systems like Raspberry Pi, which is the smallest computer to handle a large amount of data nowadays. This data has been plotted on the cloud services and then analyzed to predict the outcomes in terms of productivity, the efficiency of the farm.

C.N. Verdouw [2] presented the use of IoT technology in the field of the food industry and agro farm as far as possible. On the Earth, already the capacity of the total agriculture, food production, sensor-based systems, and so on has been already extended to its limit. So, Verdouw mentioned about how effectively we can utilize the use of IoT in the agriculture to cope up with the food problem. With the tabular form, an effective representation of the growth of atomization in agriculture and food has been mentioned. Nikesh Gondchawar and Dr. R.S. Kawitkar [3, 4] proposed the same approach of IoT in agriculture by introducing three different approaches: remote-controlled operations of farming, smart irrigation, and warehouse management by feeding live data. Sensory network using Zigbee modules and Raspberry Pi is producing such amount of live data.

Xiaohui Wang [5] introduced the agriculture-based means of production using IoT. They also introduced the different means by which production chain productivity and efficiency will get increased. Their operational efficiency will get improved by Technology-Organization – Environment (TOE) model proposed under supply chain management.

Zhao Liqiang [6] proposed wireless crop management where data processing unit will be created using TinyOs. It implements low power consumption algorithm using precision agriculture (PA). The authors in [4, 7–10] proposed PA for ideal farming using sensors and IoT frameworks along with web services. They highlighted water irrigation and planting issues as water resources are day by day becoming a critical issue. The literature included under this has a broad coverage of water management, monitoring environment under irrigation system, use of sensory systems, soil monitoring and so on that has been pointed out very numerously. Ciprian-Radu Rad [11] had also proposed the same approach of PA but for the potato crop. Rajeswari [12, 13] also mentions about the agro-based models using IoT, big data, data mining was through a mobile application, the rancher is going to receive update about the investment done in fertilizers, seeds, and so on so that production cost can be saved with proper prediction approach, and smart farming will get enabled. Ashwini Raut et al. [13] even worked on the same principle and tried to save water consumption.

Vikas Sharma [10, 14, 15] has mentioned automated drip irrigation using soil moisture sensors for okra crops or in orchards. He achieved 0.935% of accuracy in calculation with perfect soil moisture amount so that farmers can accurately manage the water content available in the soil. Harshal M. Khairnar [16–21] introduced sensor-based system to calculate the micronutrient values from the soil. They had implemented the circuit-based kit to measure N, P, and K values or the soil description. Soil fertility is also measured [22–24] to calculate crop productivity in a particular soil type using pH value. A system has been implemented to calculate the same using Arduino. It not only calculates the pH of the soil but also recommends the type of crop that can be grown in the soil.

Qiang Liu [25] introduced an automatic water retention test system for different soil types. A change in the quantity of the water contents for sandy and silty soils is tested for the retention ratio before and after. This retention ratio curve has been observed through the developed control software.

Tahar Boutraa et al. [26, 27] observed and proposed the automatic and manual water irrigation system for the wheat crops. These are controlled by humidity sensors with microcontroller that focuses on the water consumption and water loss in the soil. Measurement criteria are growth of the plant in manual and automated mode of water droplets scheme. This will conclude with the approach that is beneficial for efficient use of water.

Kristen S. Veum [28] proposed a soil health assessment tool using sensor data. It worked to calculate the visible and near-infrared (VNIR) sensory data obtained from corresponding complementary sensors to generate the scores.

Until now much of the research work has been brought to our notice to provide sensory information to the needy and to try to make up with the requirement gathering and its analysis. But the proposed system Kisan-e-Mitra is set to the standards to meet up all the needs of the agriculturists to overcome the traditional approach of soil testing [17] and to provide this facility at their doorstep. It will not only measure the micronutrient value but also generate the report for lagging micronutrients in the soil where it calculates the nature of healthy soil to increase the yield, and also recommender mechanism encourages the use of organic farming.

In contrast to physical and biological tests, compound tests for the values of N, P, K, and pH are available in most common laboratories at different taluka places. However, the 100% accuracy of getting soil data to measure its biological health is dubious and certainly depends on the chemical test kit. Accurate on-site tests may expand adoption of soil testing by growers. The objective of this investigation was to survey the effectiveness and utilization of basic physical, biological, and concoction soil well-being marker tests that can be finished nearby. Various potential soil tests were at first screened for straightforwardness and time of utilization notwithstanding accessibility of materials. Certain different basic tests for estimating soil's physical, natural, and substance properties have then corresponded to practical identical research center investigations for their capacity to recognize soils of known soil well-being attributes. Tests that contrasted well and comparing lab investigation were instructed to orchardists through exhibitions. At last, overview reaction information was gathered on the producer view of the tests.

10.2.1 Role of IoT in agriculture

The role of IoT has changed the economy because agriculture sector provides more than 75% of the income to India. Due to this current technology, multiple information has been gathered in the cloud platform, and it is always possible to access this data anywhere and at any place. Cloud is the safe place where data upkeeping is always easy with the tools available [29].

10.3 Proposed architecture

Recent surveys mention that there is no existence of any doorstep device for the farmers to carry out soil analysis and testing. It is not possible to analyze the soil quality texture using IoT kit and linger contents like micronutrients of soil.

Proposed system suggests and recommends the natural composites to fulfill the requirement of the soil and achieve gain in nutrients value. This patented innovation deals with organic farming; hence, herewith, device recommends the amount of composites to be added on to the soil.

Kisan-e-Mitra is a stylish and agile soil quality analysis and monitoring tool working on IoT and machine learning platform to assist farmers in crop management using

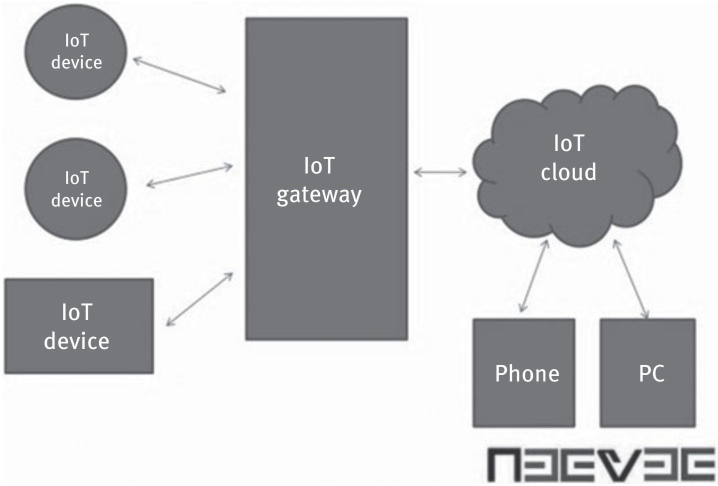

Figure 10.1: IoT architecture.

livestreaming of data such as temperature, soil moisture content, and micronutrients ratio. This enables smart farming to increase their overall yield and quality of life.

Smart farming-based agriculture IoT stick is regarded as IoT gadget focusing on live monitoring of environmental data in terms of temperature, moisture, and other types based on the sensors integrated with it. Agricultural IoT stick provides the facility in which farmers can directly implement ideal farming as such by placing the stick on the field and getting live data feeds on various devices like smart phones and tablets, and the data generated via sensors can be easily shared and viewed by agriculture consultants anywhere remotely via cloud computing technology integration. IoT stick also enables the analysis of various sorts of data via big data analytics from time to time.

10.3.1 Raspberry Pi

The Raspberry Pi is the smallest circuit-based pocket size computer which provides facility like Bluetooth and USB so that we can connect the live data collected from the sensors and get it uploaded on the cloud. IT can perform all operations that TinyOS can do in a faster way. Because of such device, live data will get connected to the Internet and can be accessed at any moment. It has different models. Based on the requirement of the application, we can choose the right option. It has generally double processor with ARM11 having certain RAM capacity. It uses GSM module for sending the data through the servers installed.

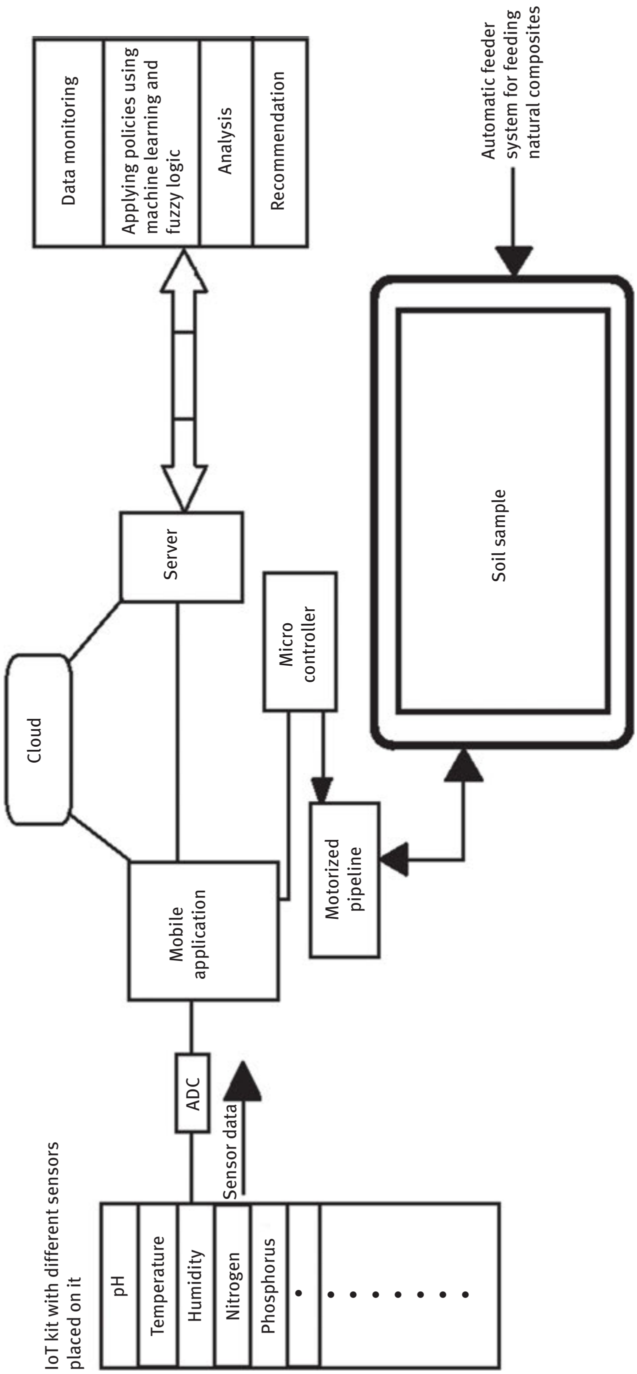

Figure 10.2: Proposed architecture for Kisan-e-Mitra.

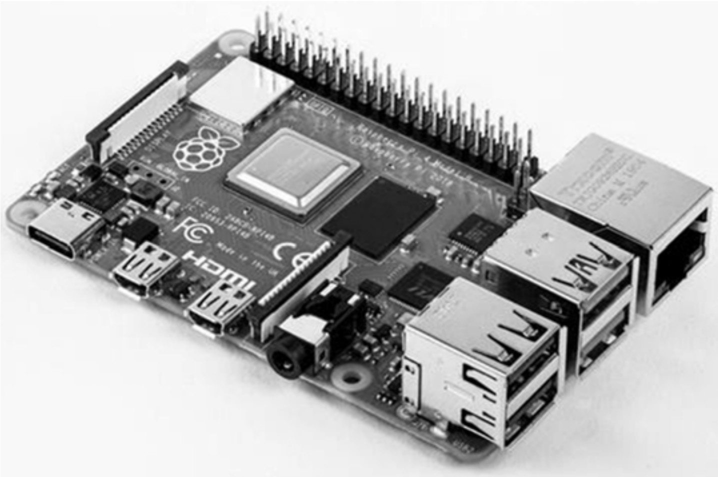

Figure 10.3: Raspberry Pi board.

10.3.2 Soil moisture sensor

This soil moisture sensor is one of the sensors that has been greatly used in the agriculture domain to measure the water content present inside the soil. Based on the types of soil, value of holding the water quantity differs in a wide range. It generally uses the electrical resistance of the soil to calculate the exact amount of water it has. Majorly before using any electrical substance or equipment, we must calibrate it to acquire the perfect value of the measuring attribute [3].

10.3.3 Temperature sensor

The LM35 is precision integrated circuit temperature sensor. Output voltage of LM35 is directly proportional to the centigrade/Celsius of temperature. The LM35 does not need external calibration or trimming to provide accurate temperature range. It is a very low-cost sensor. It has low output impedance and linear output. The operating temperature range for LM35 is −55 °C to +150 °C. With a rise in temperature, the output voltage of the sensor increases linearly and the value of voltage is given to the microcontroller that is multiplied by the conversion factor in order to give the value of actual temperature [3]. The DS18B20 temperature sensor provides 9-bit to 12-bit Celsius temperature measurements and has an alarm function with nonvolatile user-programmable upper and lower trigger points. Technical specifications: unique wire interface measures temperature from −55 °C to +125 °C; converts temperature to 12-bit digital word in 750 ms.

10.3.4 Arduino Uno

Arduino is the microcontroller-based circuit that has certain numbers of input and out pins through which we can easily extend our programming skills. It also has USB connection for serial input–output.

10.3.5 Analog to digital converter

Analog-to-digital converter (ADC) is used to convert all livestreaming data to digital form so as to manipulate the data and display the same with the help of the android mobile app.

10.3.6 Workflow of the proposed work

Kisan-e-Mitra works in five different stages. Working module starts with mounting of kit onto fixed iron rod. Kisan-e-Mitra is supporting flavor to the growers to work on calculating biological health of the soil. After switching it on, Bluetooth of the android phone has to be switched on. All kinds of different sensors are mounted onto the kit. Now as shown in Figure 10.4, in phase II, sensory data has been collected on Raspberry Pi, and through ADC convertor, analog data has been converted into digital one. At the same time in phase III, replica of the same dataset has been saved onto the cloud database. In phase IV, various machine learning techniques have been applied to the repository, and backend processing has been performed on the generated dataset. Finally, according to the policy applied as per the standard dataset value chart, soil report has been generated that is visible to the grower through the Graphical User Interface (GUI) provided on the mobile phone. Based on the report, lagging micronutrient values have been highlighted, and according to it, the recommender system will operate through the motory systems to provide essential values to the soil.

10.3.7 Unique features of the proposed system (Kisan-e-Mitra)

1. The inventive step in this system is that it successfully predicts the mixture needed to be added to the soil based on the current soil parameters that are observed.
2. A wide range of parameters (micronutrients) is considered for quality improvements such as *NPK* values.
3. Single gadget available at one-touch solution.
4. The recommender system will suggest all kinds of natural composites for organic farming.
5. The feeder will feed composites required to gain natural soil quality nutrients.

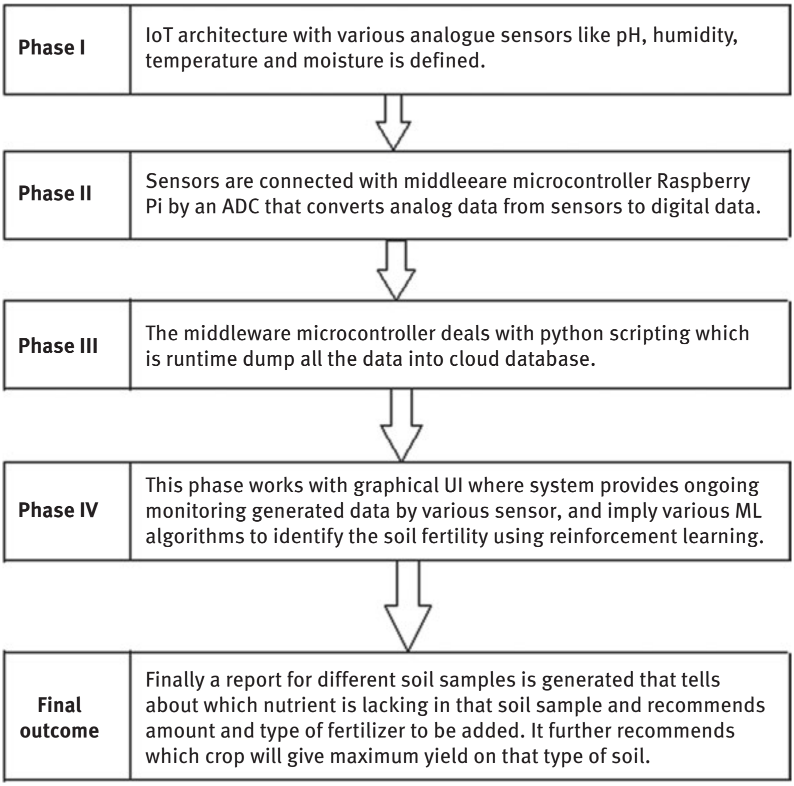

Figure 10.4: Workflow of Kisan-e-Mitra.

10.4 Experiments and discussions

Under the experiments, it is expected to get the reports with the same accuracy by the Kisan-e-Mitra and in soil testing labs. To achieve the greatest accuracy, various high-level sensors were chosen carefully and experiments have been carried out. The following standard values shown in Figure 10.5 have been set to the standards.

Tests have been carried with analogous machine learning algorithms and compared with values. A sensory dataset has been generated.

For simulation purpose, in Weka GUI, soil type has been selected to calculate for a total of 1,012 instances and obtained 99% of accuracy with the naïve Bayes algorithm.

For binary classification, accuracy can also be calculated in terms of positives and negatives as follows:

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

pH	Soil type	*N*	*N* amount	*P*	*P* amount	*K*	*K* amount
7.1	Good pH	286	Medim	5.26	Low	253	Medium
7.2	Good pH	191	Less	8.55	Low	665	High
7.18	Good pH	286	Appropriate	4.38	Low	264	Medium
8.02	Good pH	572	Excess	23.1	High	348	High
8.6	Bad pH	382	Appropriate	4.82	Low	317	High
8.79	Bad pH	477	Appropriate	3.94	Low	465	High
8.04	Good pH	286	Appropriate	2.41	Low	370	High
8	Good pH	477	Appropriate	2.85	Low	327	High
8.01	Good pH	286	Appropriate	4.16	Low	317	High
8	Good pH	334	Appropriate	5.26	Low	348	High
8.02	Good pH	572	Excess	6.36	Low	412	High
8.02	Good pH	191	Less	5.48	Low	465	High
8	Good pH	477	Appropriate	7.23	Low	475	High
7.9	Good pH	286	Appropriate	7.67	Low	422	High
7.88	Good pH	191	Less	4.16	Low	306	High
8.9	Bad pH	238	Less	3.72	Low	317	High
8	Good pH	286	Appropriate	1.97	Low	327	High
7.99	Good pH	382	Appropriate	2.19	Low	422	High
8.7	Bad pH	331	Appropriate	0.87	Low	264	Medium
8.2	Good pH	442	Appropriate	0.65	Low	359	High
8.7	Bad pH	221	Less	1.09	Low	359	High
8	Good pH	332	Appropriate	0.65	Low	232	Medium
8.02	Good pH	552	Excess	2.19	Low	211	Medium

Figure 10.5: Dataset generated for Kisan-e-Mitra.

where TP represents the true positives, TN the true negatives, FP the false positives, and FN the false negatives

$$\text{Error rate} = 1 - \text{Accuracy}$$

These measuring parameters have been completely analyzed and graphs are plotted for the same.

10.5 Conclusion and future scope

A novel smart farming enabled IoT-based agriculture tool kit Kisan-e-Mitra for soil quality analysis, testing, and recommendation in an innovative way of doing organic farming. This tool kit is highly efficient and accurate in acquiring live data of attributes such as temperature, soil moisture, and NPK values. IT will also store

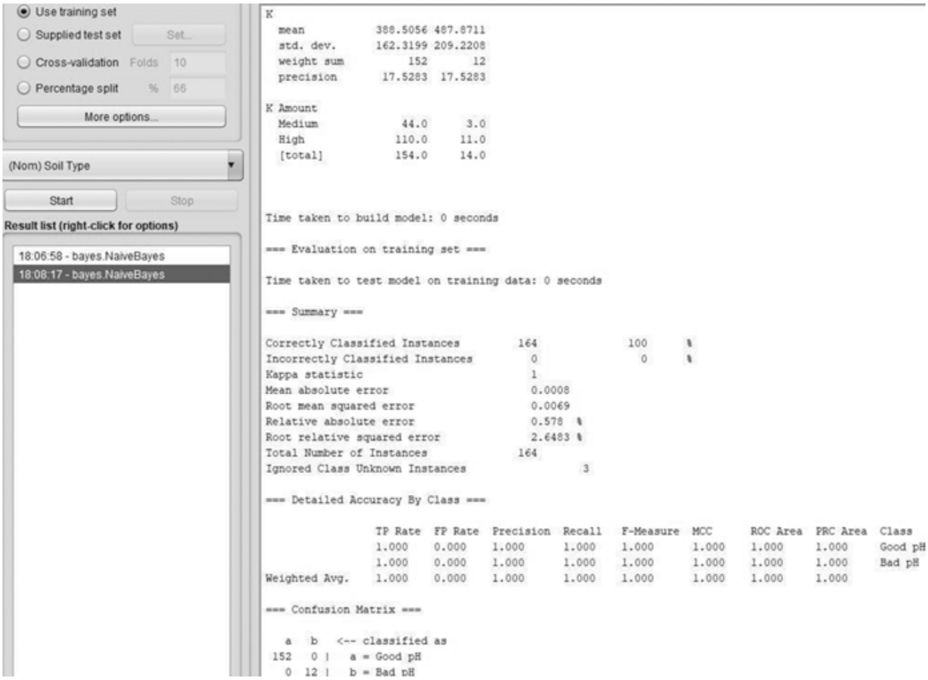

Figure 10.6: Weka GUI for naïve Bayes.

these current and backdated records on the cloud network frameworks and can be accessible at any point of time. The android mobile app is designed to access this data, and based on standard values, lagging micronutrients will be calculated. On the other hand, this will also assist farmers in increasing the farming capabilities and take utmost care of food production.

In the future, scope of proposed framework can be upgraded using more advanced chemical, physical, and biological sensors to gain more values.

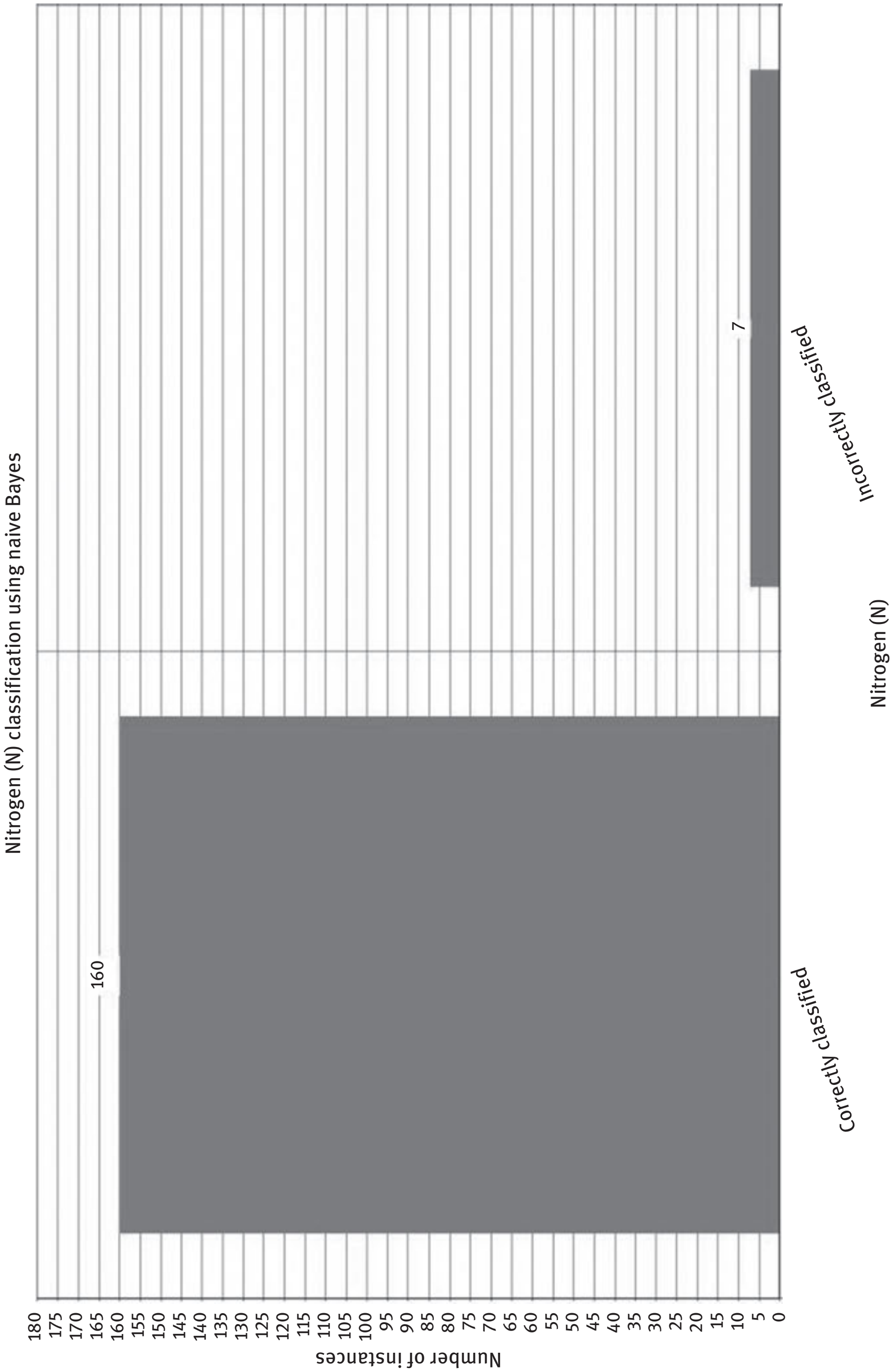

Figure 10.7: Nitrogen (N) classification.

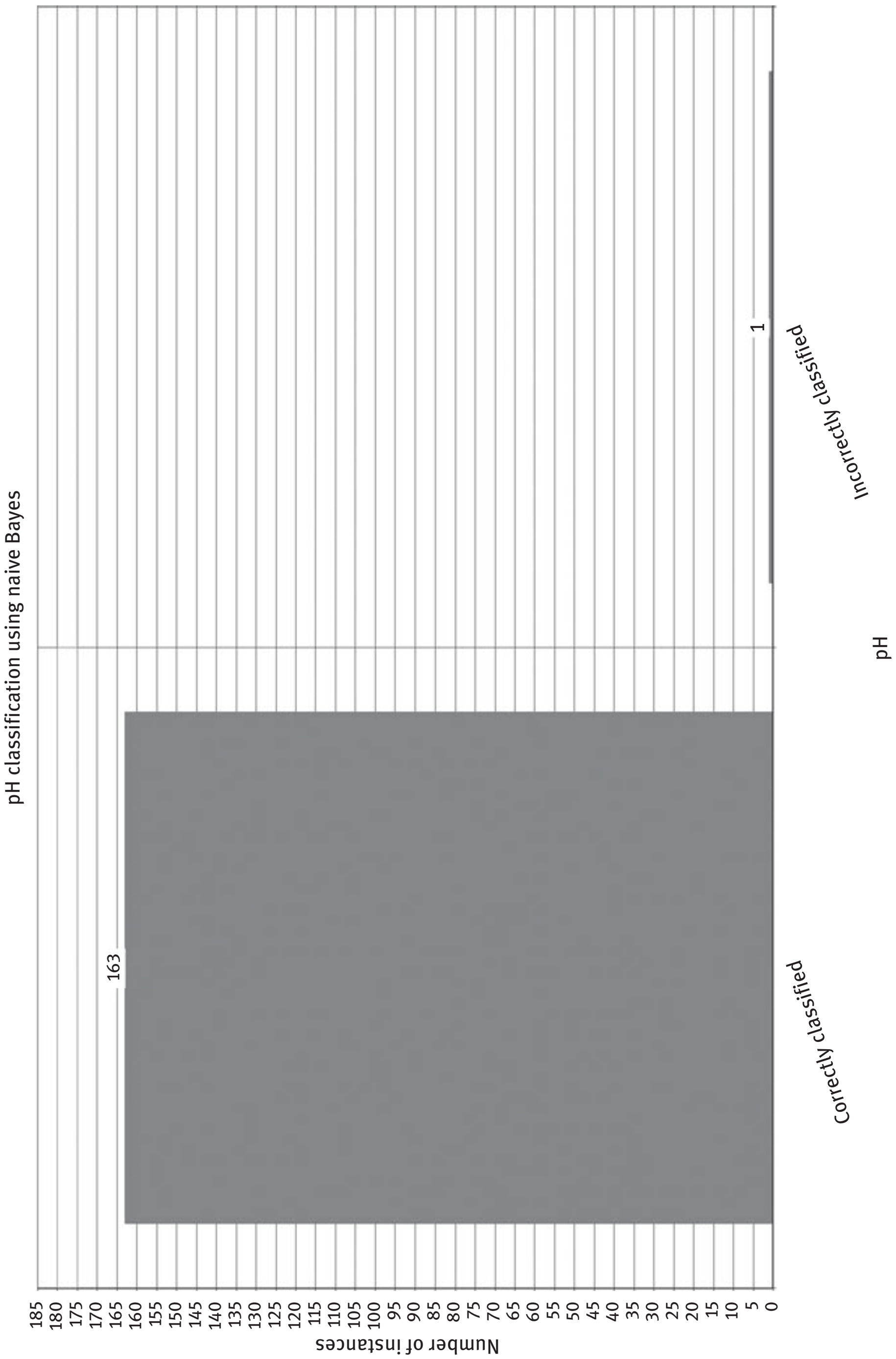

Figure 10.8: Classification using pH.

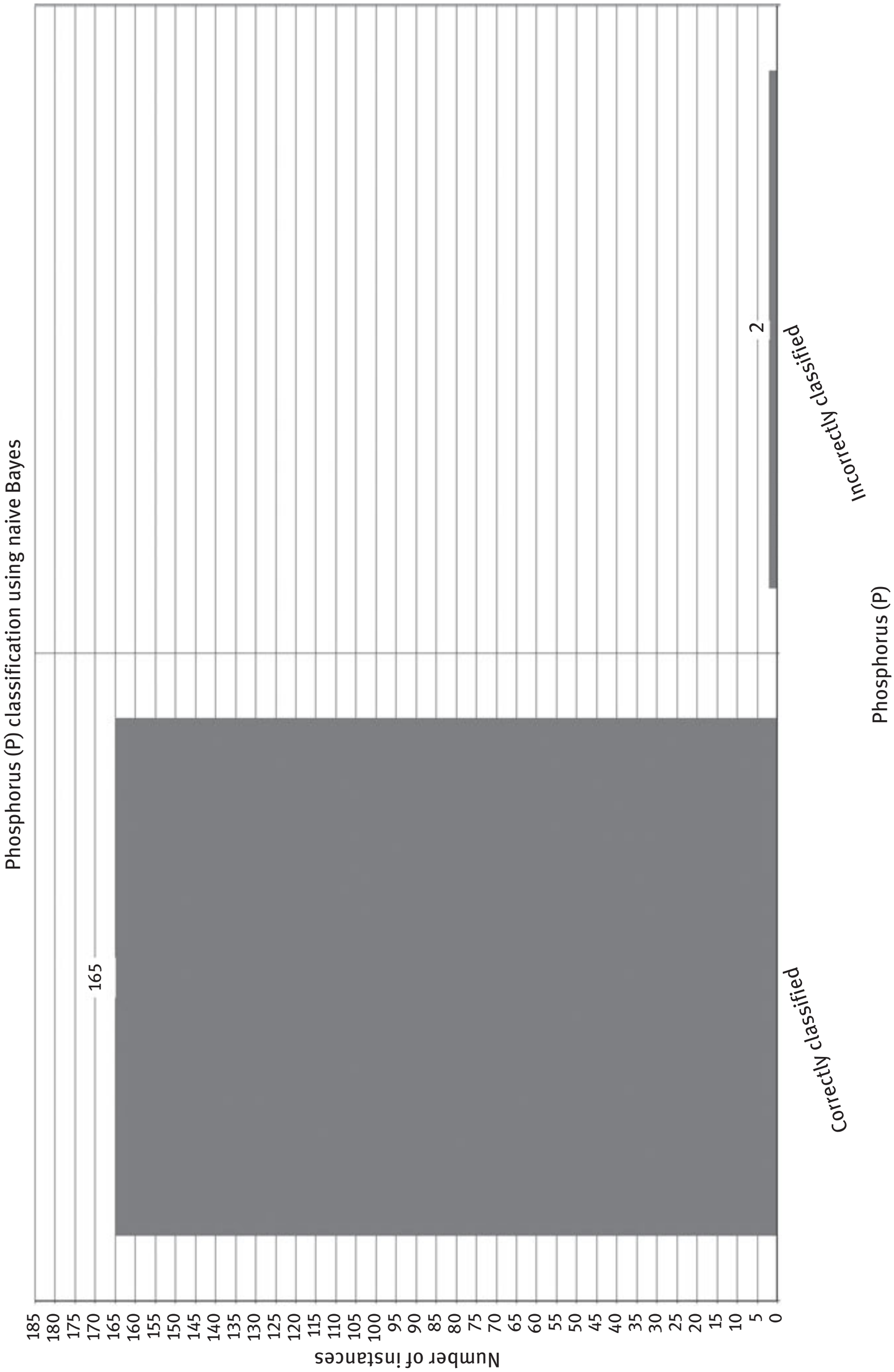

Figure 10.9: Classification using phosphorus (P).

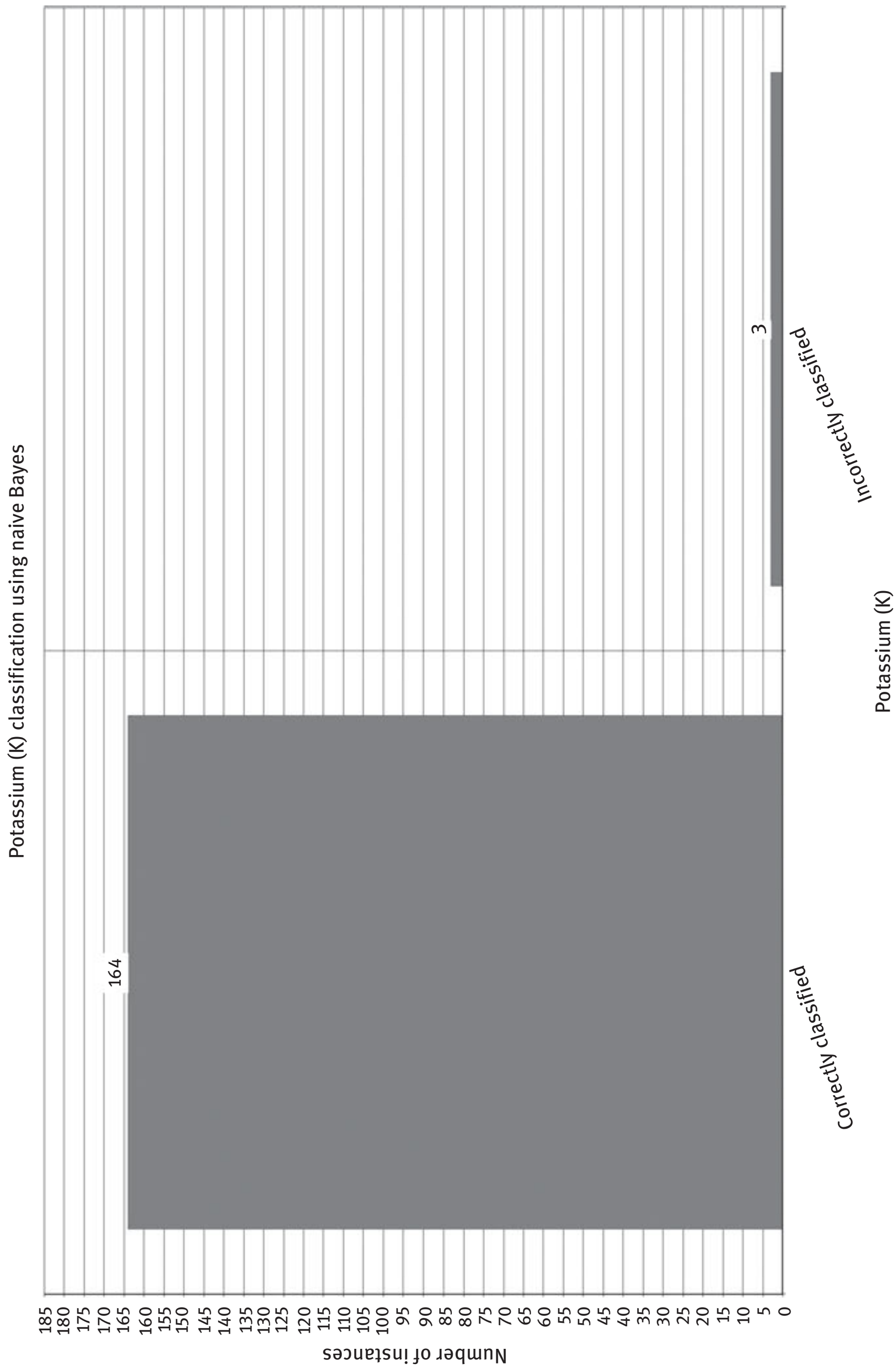

Figure 10.10: Classification for potassium (K).

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11 Artificial intelligence for plant disease detection: past, present, and future

Abstract: This chapter presents a discursive literature survey on the applications of artificial intelligence (AI) techniques in plant disease detection. The agriculture field faces many problems from cultivating to harvesting. Major concerns are various disease infections. This leads to severe yield loss with environmental hazards due to extreme usage of insecticides. With insane expansion of human population, the demand for food is incessantly surging. Conventional techniques used by farmers are not only adequate to satisfy the augmenting demand but also hamper the soil by intense use of hazardous pesticides. Besides, conventional techniques, AI gives many advantages in disease detection. In 1983, computer application was used to solve a problem in agriculture for the first time. Since then, numerous approaches have been designed to figure out a large number of problems in the field of agriculture. Furthermore, many databases and decision support systems have been developed. Out of these, AI techniques have been conveyed to deliver results with better accuracy and robustness. In addition, it enabled researchers to detect the complicated details of each condition and offer a solution that could be a perfect fit for the respective problem. Different AI techniques like convolutional neural network, artificial neural network, and deep learning have been successfully used for disease detection in rice, wheat, maize, cotton, tomato, peas, potato, cucumber, cassava, berries, peach, grapes, olives, mango, banana, apple, sweet paper, tea, and so on. This chapter discusses various AI techniques that were developed and used in agriculture for plant disease detection and discourses in its future to achieve precision in farming.

Keywords: plant disease detection, expert systems, convolutional neural network, deep learning, neural network

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https://doi.org/10.1515/9783110691276-011

11.1 Overview

The agriculture domain is an area of great importance, where globally ~30.7% population is directly involved with 2,781 mha of cultivated land. It faces several difficulties including disease infections, insect–pest management, weed management, insecticide–pesticide controls, and irrigation and storage management. from sowing to harvesting. Among these, the major issues are disease infections and insect–pest management. Plant diseases are not only a danger to global food protection, but they may also have devastating implications for small and marginal growers whose lives rely on crops [1]. Agriculture is a challenging domain in which conditions cannot be simplified to imply a specific approach. In 1983, the first time application of computer in agriculture was reported [2]. Furthermore, diverse mechanisms have been promoted to solve plant diseases and other deadly problems in agriculture. Among these methods, artificial intelligence (AI) had the most outstanding performance in terms of precision and robustness. AI techniques helped to locate the root of the problems and devise strategies to solve that problem. Consequently, there was a ray of hope to eliminate complex issues. Demand on the agriculture field would grow with the ceaseless rise in the population. Thus, agro technology and precision farming have become even more important in today's world. Currently, South Korea, North America, and China are spending lots of money in adopting more digital technology in agriculture. The agriculture domain is one of the most significant fields of India, promoting all other fields and increasing its significance in far-reaching areas. Liakos et al. [3] mentioned the term "digital agriculture," which means using modern and advanced technologies to improve agricultural value chain.

11.2 Different types of plant diseases

Many biotic (living organisms like fungi, viruses, bacteria, and nematodes) and abiotic (environmental factors such as high temperature, salinity, drought, iron deficiency, low soil fertility, and pH) factors induced numerous plant diseases. Among them, biotic factors are more harmful causing the highest yield losses. Furthermore, it is divided into mainly three categories: fungi, viruses, and bacteria. Fungal-like organisms cause more plant diseases than other biotic factors with over 8,000 species shown to cause fungal diseases. Besides, many types of bacteria cause plant disease. Bacterial plant diseases are explicit in general symptoms from others [4]. Viruses are the most damaging biotic factors because once the plant is infected with any virus, it cannot be recovered by chemical practices, and the whole plant will be discarded to stop the spread of infection. Fungal spores are spread through the air while bacteria can travel through splashing water. Besides, viruses are transmitted through specific insect vector.

11.3 Datasets

Before AI techniques can be deployed for plant disease detection, they need to be trained with large datasets that can be generated from different plant leaf images such as infected and fresh. This will allow models to differentiate between infected and fresh plants. These datasets often exist as images of different plant species and in different combinations like infected and healthy. The PlantVillage dataset (PVD) has more than 50,000 healthy and unhealthy leaf images [5]. Recently, Singh et al. [6] developed a dataset of 2,598 images of 17 different classes of 13 crops (Figure 11.1). Another important thing associated with plant images is image classifiers. The images available in datasets are colored and vary in size. To train any models, images are resized or normalized (224 × 224 or 299 × 299 pixel) using different image classifiers like DenseNets, residual neural network (ResNet), and Visual Geometry Group (VGG) net. Normalization is performed to balance pixel values in the range of 255, which is favorable for neural networks (NN), convolutional neural network (CNN), and so on. On top of that, categorical variables are mapped as per models.

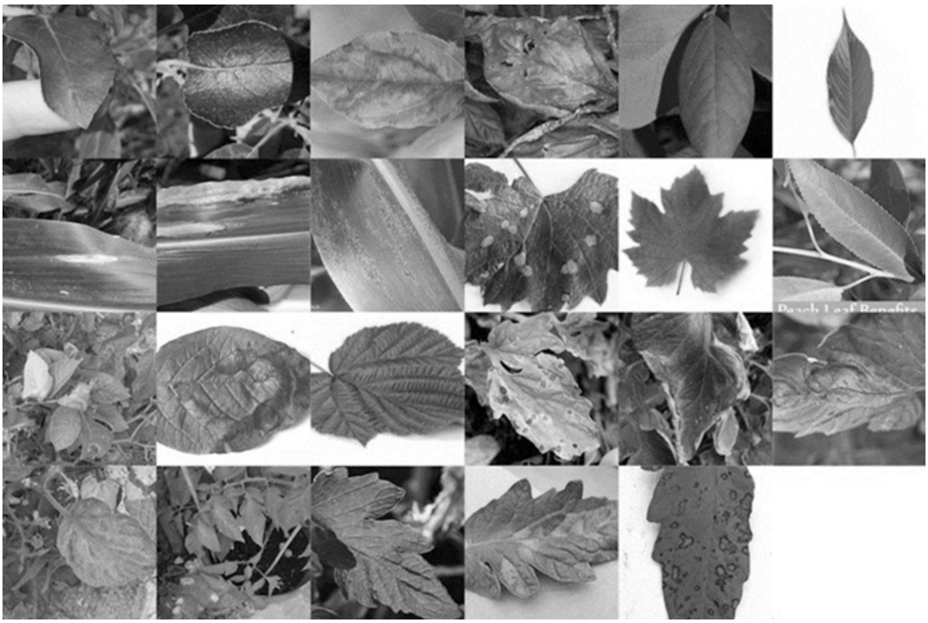

Figure 11.1: Different leaf images from the PlantDoc dataset [6] (available at: https://github.com/pratikkayal/PlantDoc-Dataset).

11.3.1 VGG net model

Simonyan and Zisserman [7] developed VGG net model. The model obtained a 7.5% error rate ranked second in the competition. Usually, the paradigm is symbolized by its simplicity, with just 3×3 N arrays combined. Max pooling handles minimization of volume size (downsampling). In addition, there are fully connected two layers both with 4,096 nodes.

11.3.2 ResNet

[8] implemented the ResNet concept. It ranked first with 96.43% accuracy. It is a network-in-network architecture with global average pooling at the end. The model uses residual units to create the web-like micro-NN [8]. This allows abstracting the data from more complex structures. ResNet with its shortcut connection is deeper than VGG network. The depth of the model takes care of vanishing gradient problem. The local gradient in ResNet*XX* versions is 1. In 2016, the ResNet upgrade would be more reliable to use identity mappings (He et al. 2016).

11.3.3 Inception V4

[9] introduced "Inception" concept in the GoogleNet architecture. It is considered as the simplest version of GoogleNet architecture – Inception VN, where N is version number. Later, improved version of Inception V4 was reported by Szegedy et al. [10]. This architecture is combined with residual connections whose objective is to accelerate the training of Inception networks. The Inception model consists of four levels of parallel layers: 1×1 convolutional layer, 3×3 convolutional layer, 5×5 convolutional layer, and max pooling. The 1×1 convolutional layer is used for depth reduction.

11.3.4 DenseNet

[11] acquainted with CNNs architecture with all layers interconnected in a forward manner to allow minimum information loss. The mapping in-between layers consisted of a collection of high-resolution images. Due to naturally created progressing flow, the features generated from these images were fetched as input to consequent layers. This setup came with advantages like annihilating gradient problems and less number of parameters use. Consequently, DenseNet comprising flawless 121 layers was created.

11.4 Plant disease detection

Plant diseases are often a subject of significant concern to a farmer. To detect a disease in plant and propose the measures, companies consulted subject matter experts for their guidance. Globally, advance systems have made easy detection possible and their counters as well. In the early twentieth century, traditional techniques solved this using plant leaf images. The whole process includes five steps (Figure 11.2): Starting with image gathering via clicking pictures in the field sometimes under controlled conditions. The collected images will be used to prepare large image dataset. In the second step, image was preprocessed; it includes noise removal, cropping, resizing, image enhancement, and transformation. Furthermore, in the third step of image segmentation, the image was subdivided into its constituent objects or parts. Otsu's thresholding and *k*-means clustering are the most common techniques used for segmentation. In the fourth step of feature extraction, different features like color and textures were used. These features were further used in the classifier in the fifth step. Support vector machine (SVM) and artificial neural network (ANN) are the most commonly used classifiers by researchers. Figure 11.3 shows that the frequency of image-based plant disease in agricultural research has increased almost fivefold in 2019. Earlier, rule-based expert systems were developed for different crops like rice, wheat, and potato [12–14]. An algorithm was developed using AI techniques that facilitated experts in their processes [15]. It was a robust, intelligent, and computerized

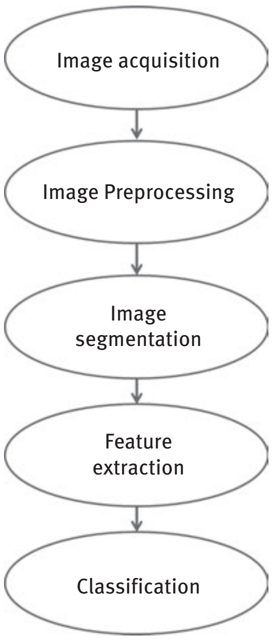

Figure 11.2: Steps followed in traditional ML techniques.

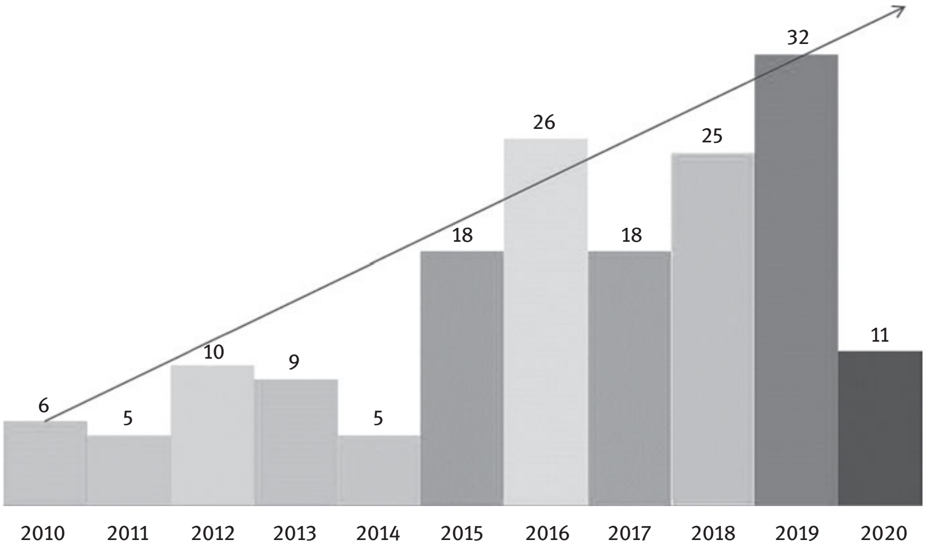

Figure 11.3: Last 10 year's trend for image-based plant disease detection. The data are obtained through searching the image-based plant disease detection on PubMed (Dated 27/05/2020).

decision-making device. The extremities of such systems potential were unimaginable that claimed to take place of field experts. Details of expert systems developed for different crops were listed in Table 11.1.

Table 11.1: List of expert system developed in agricultural domain.

System name	Crop name and area	Reference
PLANT/tm	Diagnosis of weed in turf	[16]
COMAX	Cotton crop management	[17]
CALEX/ cotton	Irrigated crop management	[18]
BDM-EXPERT	Water shortage problems	[19]
POMI	Integrated pest management of apple orchards	[20]
VEGES	A vegetable expert system	[21]
CROPES	Supply of water and other services, atmosphere, soil properties, and factors important to farmers	[22]

Table 11.1 (continued)

System name	Crop name and area	Reference
CITEX	Citrus crop management	[23]
LIMEX	Lime crop management	[24]
PADDY	Paddy production management	[25]
NEPER	Wheat crop production management	[26]
Diagnos 4.0	Diagnose the pests and diseases of major crops	[27]
AMRAPALIKA	Indian mango: diagnosis of pests and diseases	[28]
Crop-9-DSS	Pest and diseases with control measures, fertilizer recommendation system, and so on for leading crops	[29]
Dr. Wheat	Pakistani wheat: diagnosis of diseases and pests	[30]
AGREX	Provide accurate and timely guidance to farmers	[31]
TOMATEX	An expert system for tomatoes	[32]
CUPTEX	Management of cucumber disorders	[33]

Earlier, Khan et al. [30] developed Dr. Wheat, an online expert system, specifically for accurate analysis of Pakistani wheat diseases. Sannakki et al. [34] reported a fuzzy logic approach coupled with image processing to detect percentage of infection in leaf. Tilva et al. [35] developed a fuzzy model for disease detection via weather forecasting. Al-Hiary et al. [36] and Bashish et al. [37] engineered a setup with *k*-means clustering algorithm. Furthermore, different ANN-based models were designed to deal with diseases along with pest control for many crops [38–42]. Some hybrid systems were also suggested: Huang [43] proposed an image processing model coupled with ANN model to classify phalaenopsis seedling diseases. Using traditional techniques of machine learning (ML) and image processing led to inadequate performance consequences. Deep learning (DL) is the fresh unraveling in ML. It guarantees better improvement in image classification accuracy alongside integration with live application support. The major alterations are illustrated in Figure 11.4. Plant disease detection using different models and datasets was presented in Table 11.2. Kawasaki et al. [44] developed a system to detect diseases in plant. The model's accuracy was tested with almost 1,000 cucumber leaves' pictures. This resulted in an outstanding 94.9% rate validated using fourfold cross-technique. When the same group of researchers used 7,250 images, with two CNN models achieving an average of 82.3% accuracy, seven different types of diseases in cucumber were detected.

Sladojevic et al. [41] structured pretrained CaffeNet CNN model with over 3,000 images depicting 13 kinds of diseases in several crops. The CNN model by 96.3%.

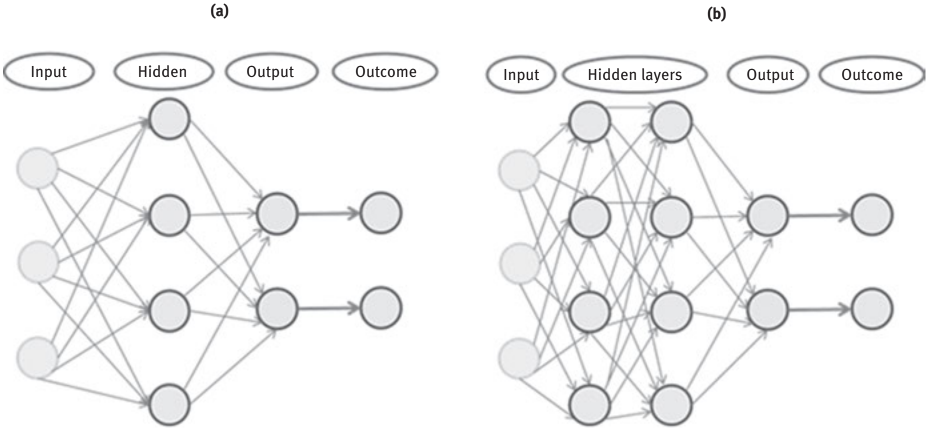

Figure 11.4: Difference between traditional ML and DL techniques. (a) Traditional ML with one hidden layer and (b) DL with two or more than two hidden layers (source [69]).

Table 11.2: Details of plant disease detection using different models and datasets.

Crop	Dataset	Models used	Accuracy	Reference
Cucumber	Own	Custom CNN	Up to 94.9%	[44]
Five crop species	Websites	CaffeNet	96.3%	[41]
Fourteen crop species	PVD	AlexNet and GoogleNet	Up to 99.34%	[1]
Cucumber	Own	CNN1 and CNN2	83.2%	[45]
Tomato	Own	AlexNet, ZFNet, VGG16, GoogleNet, ResNet50, and ResNet101	Up to 86%	[46]
Tomato	PVD	AlexNet and SqueezeNet	Up to 95.65%	[50]
Tomato	PVD	AlexNet and GoogleNet	Up to 99.18%	[54]
Banana	PVD	LeNet	99.72%	[47]
Apple	PVD	ResNet50, VGG19, VGG16, and Inception V3	Up to 90.4%	[48]
Wheat	Own	Two proposed DMIL-WDDs and CNN models	Up to 97.95%	[55]
Rice	Own	Custom CNN	95.48%	[55]
Maize	Own	Pipeline of CNNs	96.7%	[52]
Cassava	Own	Inception V3	Up to 93%	[53]

Table 11.2 (continued)

Crop	Dataset	Models used	Accuracy	Reference
Olive	PVD, Own	LeNet	98.6 ± 1.47%	[51]
Apple	Own	Modified AlexNet	97.62%	[56]
Maize	PVD, websites	GoogleNet and Cifar10	Up to 98.9%	[57]
Tomato	PVD	AlexNet and VGG16	97.29%	[58]
Tomato	PVD	RGB-based CNN model	86%	[59]
Cucumber	PVD, websites, own	Custom DCNN and pretrained AlexNet	94%	[60]
Wheat	Own	ResNet50	Average 87%	[61]
Fourteen crop species	PVD	ResNet with 50, 101, and 152 layers, VGG16, DenseNets, and Inception V4	Up to 99.75%	[62]
Nineteen crops	PVD	Inception V3 and MobileNet	Up to 92%	[63]
Banana	Own	ResNet50, Inception V2, and MobileNetV1	90%	[64]
–	Public dataset	LeNet, AlexNet, and Inception V3	98%	[65]
Fourteen crops	PVD	VGG16, Inception V3, MobileNet, and proposed model	Average 91.2%	[66]
Tomato	PVD	CNN	98%	[67]
Sugarcane	Own	Inception V3, VGG16, and VGG19	90.2%	[68]

Mohanty et al. [1] resulted in 38 classifications with 14 diseases of 14 crops, at 96.4% accuracy. Both the models were loaded with computer-supported three-dimensional images, monochrome images, and images with several splitting ratios and trained AlexNet and GoogleNet. The GoogleNet with RGB images and transfer learning achieved maximum accuracy of 99.3%. Fuentes et al. [46] developed a live model that can uncover tomato disease and pest recognition. It contained 5,000 images from different locations and conditions. ResNet50 with Region-based Fully Convolutional Networks (R-FCN) reached 86% accuracy. Amara et al. [47] used 3,700 images with LeNet architecture to unearth two categories of diseases in banana leaf images from the PVD that obtained 99.72% accuracy by using 50% for training dataset and remaining for test set. Another PVD use was shown by Wang et al. [48] that encounter the worse conditions of apple black rot disease. They trained four different models such as fine-tuned VGG16, VGG19, Inception V3, and ResNet50 that generated an accuracy of 90.4% with fine-tuned VGG16. In 2017, the Wheat Disease Database 2017 was developed with 9,230 images divided into seven different wheat disease classes [49]. Durmus et al. [50] used both AlexNet and SqueezeNet models for disease detection of the tomato plant. They used 18,000 images of 10 different disease classes from PVD and achieved accuracy of up to 95.65%. Liu et al. [49] used 500 field images of rice leaves and stems (healthy and diseased) and trained with custom deep CNN model with different pooling strategies. The result was compared using other techniques such as SVM, standard backpropagation algorithms, and particle swarm optimization. With these techniques, accuracy was reduced to 95.48% confirmed with 10-fold cross-metrics. Using different DL techniques and different datasets and models, researchers achieved higher accuracy in different crops such as apple leaf diseases, northern leaf blight disease in maize crop, cassava, and leaf scorch on olive tree leaves [49, 51–53].

Zhang et al. [57] used 500 different images of maize crop collected from PVD and online websites. They used GoogleNet and Cifar10 models, which distinguished accurately with 98.9% and 98.8% accuracy, respectively. In 2018, four image classifiers such as VGG16, Inception V4, ResNet, and DenseNet were compared, and DenseNet was found to be the best performing model with the accuracy of 99.75% [62]. Furthermore, Gandhi et al. [63] reported generative adversarial networks; it can be used for augmenting the dataset. This lifted the barrier on number of images that can be used with training models. Ferentinos [70] reported the most successful model architecture VGG CNN using public data of 87,848 photographs that gave an unbelievable rate of 99.53% accuracy. Arsenovic et al. [71] reported largest datasets containing 79,625 leaf images taken from different angles, daylight hours, and so on. There were two approaches that ensured a considerable increase in number of images, which gave rise to infamous NN. The NN architecture produced results with 93.67% accuracy. Selveraj et al. [64] developed six different models from 1,800 field images of 18 different parts of banana plant. Two models such as ResNet50 and Inception V2 surpassed MobileNetV1 in performance with an accuracy of more than 90%. Recently, Adit et al. [65] compared three models, namely, LeNet, AlexNet, and Inception V3 using 76,000 diseased plant leaves' images. Inception V3 reported enhanced performance in comparison to other two models with 98% success rate. Furthermore, Panigrahi et al. [72] used supervised ML methods such as naive Bayes , decision tree, *k*-nearest neighbor, SVM, and random forest (RF) for maize plant disease detection. Among these RF has the best accuracy rate of 79.23%.

11.5 Conclusion and future line of work

The plant detection disease, using variety of AI techniques, studies could be better dealt with sections created by the crop or dataset. Many crops like rice, wheat, maize, cotton, tomato, peas, potato, cucumber, cassava, berries, peach, grapes, olives, mango, banana, apple, sweet paper, and tea have been used in different studies. Among these crops, rice, maize, and tomato are the most used crops as they suffer

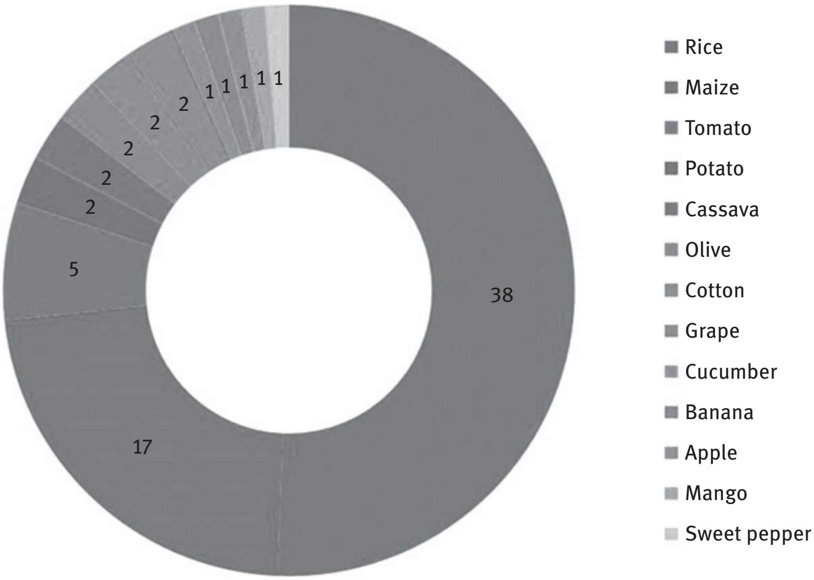

Figure 11.5: The deep learning techniques used in different crops. The data are generated through searching deep learning for each crop on PubMed (dated 27/05/2020).

from maximum contamination (Figure 11.5). Researchers have assorted plants based on relevant diseases [1, 62, 63]. Out of all datasets available, PVD is the most preferred one for plant disease detection study. However, some researchers generated own datasets satisfying different prediction pattern. Most of the researchers used different DL models for the classification of diseased images. The reason is that it is vital to diagnose when the plant is infected and recognize the disease to assess the quality treatment for these situations. Some research papers targeted and implemented their model on more portable devices like mobiles. It can be helpful for farmers to implement the model in real time, Especially in developing countries, technologies are inadequate. Appropriate machinery for diagnosing disease. So, the best option is a lightweight model that is completely implemented on portable devices.

This chapter presents the overview of different datasets, classifiers, and methods used by various researchers for plant disease detection. In the last 34 years, numerous researches have been conducted in agriculture domain. This chapter was designed to render such work as clear as possible with the descriptions of the different AI techniques. In the early 1980s and 1990s, the systems recommended by industry were more common. Although in 1990, the main role was performed by ANN models and fuzzy inference systems. While, in recent years, the usage of hybrid structures such as image processing combined with ANN or CNN is implemented. This shaped into more efficient and reliable processes that operate in real time. Future work is steered with advanced techniques so that conventional agriculture can shift toward low-cost precision farming.

Abbreviations

AI	Artificial intelligence
ANN	Artificial neural networks
CNN	Convolutional neural networks
DenseNets	Densely connected convolutional networks
DL	Deep learning
DT	Decision tree
GANs	Generative adversarial networks
KNN	*K*-Nearest neighbor
mha	Million hectares
ML	Machine learning
NB	Naive Bayes
NIN	Network-in-network
NN	Neural networks
PVD	PlantVillage dataset
RF	Random forest
ResNet	Residual networks
SVM	Support vector machine
TL	Transfer learning
VGG	Visual Geometry Group

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Sapna Nigam, Rajni Jain, Sudeep Marwaha, and Alka Arora

12 Wheat rust disease identification using deep learning

Abstract: Automated image-based tools are required when a human assessment of plant disease identification is expensive, inappropriate, or unreliable. Thus, there is a need to recognize cost-effective automated computational systems and image-based tools for disease detection that would facilitate advancements in agriculture. Deep learning (DL) is the deep neural network that uses multiple levels of abstraction for hierarchical representation of the data. Convolutional neural network model is used, in this chapter, on 2,000 images to identify the wheat rust disease in an unseen leaf image. The results show that DL has the potential to identify plant diseases with much higher accuracy.

Keywords: plant disease, wheat rust, CNN, deep learning, artificial intelligence

12.1 Introduction

The emerging challenge to the food security due to the decrease in annual crop production has become a topic of concern for the governments worldwide. Many known biotic and abiotic factors play a significant role in the crop loss, of which the plant diseases are the considerable ones. Traditionally, crop inspection and plant disorders identification were performed by farmers or experts with their naked eye. This requires detailed knowledge of disease symptoms and the experience of actual disease identification. Even with experience, this manual method is not feasible for larger fields as it requires continuous monitoring. Due to the variation and complexity of similar disease symptoms, even the agronomists or plant pathologists fail to detect specific crop diseases accurately with naked eyes. Automated image-based tools are required for the identification of complexity in plant diseases because human assessment can sometimes be inappropriate and unreliable [1, 2]. There is a need for developing cost-effective automated computational systems and image-based tools for disease detection that would facilitate advancements in agriculture [3]. In this new era of computation, in recent years, implication of artificial intelligence (AI) has been growing fearlessly and

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https://doi.org/10.1515/9783110691276-012

contributes to the development of innovative methodologies and models among which deep learning (DL) is the most prominent one [4]. With DL, computational models use the different levels of abstraction for the hierarchical representation of data. This chapter emphasizes the potential of DL to identify plant diseases with much higher accuracy.

The four phases involved in plant disease identification are namely image acquisition, image preprocessing, features extraction, and classification [5]. In image acquisition, the acquired images are converted into the preferred output format for further processing. Images may be self-acquired by authors or maybe any benchmarking dataset such as the PlantVillage database [6]. The procedure of image preprocessing aims at highlighting the region of interest (disease infected area) in plant leaves [7]. Image preprocessing commonly involves image segmentation [8–11], image enhancement, and color space conversion. The image of a leaf is filtered from unnecessary background, and RGB colors are converted into color space parameters [12, 13]. Furthermore, that image is segmented to a meaningful part, which is much easier to analyze. Unfortunately, removal of background is quite difficult and in some scenarios, automation of the system performs poorly due to user intervention [13]. In the case of feature extraction, feature vectors are constructed from the features extracted from the images manually. This type of extraction could be statistical or structural, for example, in the use of color moments in the extraction of color statistics [14], the extraction of all multiscale features is being done by combining Gabor transform and wavelet transform [15]. Many previous studies have also reported the use of gray-level co-occurrence matrix [14–18] to extract texture features. However, advantage of DL is the automatic feature extraction, which ultimately holds a good contribution in higher accuracy when compared with other conventional techniques discussed [19–25].

The last phase of plant disease identification is a classification where the classification model is implemented to identify the existing plant disease in the images. The model used for the identification must be well trained with learning algorithms and must have already seen disease images. Techniques for disease identification can be mainly classified into two types: image processing-based techniques and machine learning techniques. For disease identification, image processing techniques are necessarily followed by some machine learning methods that can perform on large datasets. On the other hand, machine learning methods can work on image-based datasets as well as textual attribute-based data that do not require an image. For disease identification using attribute-based tables, one need not use image processing techniques, but other data cleaning and preprocessing should be followed. In machine learning, algorithms are capable of learning on their own from input data according to the objective. In machine learning, high performance along with statistical pattern recognition creates new opportunities in the agriculture domain with their improved sensitivity toward plant disease detection. The *k*-nearest neighbors [15, 26], support vector machine [12, 16, 27], and artificial neural network (ANN) [28–30] represent the commonly used learning algorithms as per the literature. On the other hand, neural networks, which understand complex data, have found its applications in extraction and detection of patterns that are quite difficult to be observed by the human brain or other computer techniques. Moreover, the features like adaptive learning, real-time operations, and self-organization increase the acceptability for ANNs. ANN is a well-organized model comprising different layers connected to its consecutive layer. In this chapter, authors emphasize on the application of DL, particularly on the convolutional neural network (CNN), for developing a model for plant disease identification.

12.2 Deep learning and crop disease identification

In plant pathology, the implementation of DL in leaf image classification and plant disease identification has started to gain momentum in recent years. In this approach, during the training phase, feature extraction from the data is done automatically. To verify the superiority of DL models over state-of-the-art methods, we have reviewed both small and large dataset studies containing 500–87, 848 images [31–33]. A literature review on DL shows its better accuracy and efficiency over other techniques [19]. The conventional machine learning techniques and image processing techniques are only successful under limited and constrained systems. A comparison study on the CNN models and conventional pattern recognition techniques in plant identification using three different databases concluded that CNNs outperform the conventional methods [34].

Nigam et al. [35] reviewed the different implementation of DL in agriculture domain for identification of plant diseases and developed a CNN model to perform plant disease identification using wheat crop images of healthy leaves and yellow rust infected leaves through DL. The use of DL includes improvements in performance and high computational accuracy. Some factors affecting the CNNs performance in identification of plant diseases are limited annotated datasets, symptom representation, covariate shifts, image background, symptom segmentations, image capture conditions, multiple simultaneous disorders, symptom variations, and disorders with similar symptoms [36, 37]. In real-life conditions, the systems developed through DL have high performance and precision in detecting specific plant diseases. It can even be operated through a user-friendly mobile application for the detection of multiple diseases in plants [37, 38]. DL techniques can achieve accuracy between 90% and 99%.

DL is the deep neural network that learns the hierarchical data representations with the number of abstraction levels [39, 40]. The application of DL in plant pathology and specifically on leaf image classification and plant disease identification has started gaining momentum in recent years. One of the most powerful and basic DL tools for modeling complex processes such as image-based disease identification is CNNs.

12.3 Convolutional neural networks

In the case of image classification, CNN is more efficient than other DL models because of a smaller number of parameters involved and automatic feature extraction without any human supervision. A CNN mainly consists of three layers: convolution layer, pooling layer, and fully connected layers [19]. A CNN model has two components: feature extraction and classification (Figure 12.1). The convolution layer and pooling layers perform the feature extraction from the input images, whereas fully connected layers have their role in classification of the images into predefined classes.

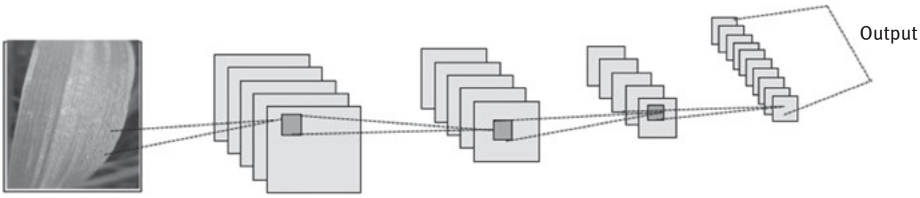

Figure 12.1: Convolution neural network architecture.

The different layers involved in CNN are explained as follows:

1. *Convolution layer:* This layer extracts features automatically from each input image. It basically consists of a set of learnable filters and learns the relationship between features using kernel or filters to produce a feature map. Each learnable filter is applied to the raw pixel values of the image in a sliding window manner, and computes the dot product between the filtered and input pixel. This results in a two-dimensional activation map known as a feature map. In simple terms, the network learns filters (i.e., edges and curves) that activate when there are known features in the input image. The values of these filters are learnt by the CNN during the process of training. Rectified linear unit is a activation function with output $f(x) = \max(0, x)$ that is used to introduce the nonlinearity in the CNN model.
2. *Pooling layer:* This layer reduces the size of convolution maps by downsampling, which decreases the training time and combats overfitting by retaining only the valuable information to process further. Max pooling is a commonly used pooling type, which takes the max value in the pooling window, whereas a mean value is taken in case of average and sum pooling. The output is given in the form of the maximum activation value and hence reduces the dimensionality of the feature.
3. *Fully connected layer:* Final pooling layer output (three-dimensional matrix) is flattened into a one-dimensional vector and that becomes the input to the fully

connected layer. These features are then combined to create a model. In the end, SoftMax or sigmoid activation function computes the predefined class scores and classifies the image into a predefined class.

12.4 Parameters and hyperparameters in CNN model

DL comprises parameters and hyperparameters. Parameters are the configuration variables whose value can be estimated or learned from the data, whereas variables of hyperparameters determine the network structure of a model. These are decided before the training of the network. Hyperparameters related to a network structure are as follows:

- *Batch and batch size:* It is the total amount of training examples present in a single set. Batch size is the number of subsamples given to the network for parameter updates. The optimum size is determined based on experiments as shown in Figure 12.1.
- *Epochs:* It refers to the times the training data is given to the network while training the model. Even though the training accuracy increases on increasing epochs, at some point, the validation accuracy starts decreasing. At that point, more epochs will lead to overfitting of model.
- *Hidden layers and units:* Middle layers are present between the input and the output layer. Layers can be added until the test error improves.
- *Activation function:* It introduces the nonlinearity in a model, which allows the learning of nonlinear prediction boundaries. SoftMax is used more often in the output layer while making multiclass predictions.
- *Learning rate:* It is defined as the speed of a network in updating its parameters while learning in a model. Usually, a decaying learning rate is mostly preferred.
- *Momentum:* It gives information about the direction of next step with the help of prior knowledge about previous steps and prevents oscillations. A momentum of 0.5–0.9 is generally chosen while training a model.

12.5 Software and hardware requirement

With an increasing focus on DL studies, many software prevail in the industry for automatic disease identification. Caffe, Tensorflow, and frameworks are used along with popular Python libraries such as Keras. MATLAB is used for the efficient preprocessing of images. Most recently, DL libraries are introduced in R software too. Caffe, Keras, Tensorflow, Theano, and Deeplearning4j are popular software that can be used for disease identification using CNN architecture models. Usually, the hardware requirement is quite a challenge in DL. It needs high computational machines for faster training of the model. DL algorithms are mostly seen being implemented on the NVIDIA® graphical processing units in the Linux environment.

12.6 Case study of wheat rust

In this case study, 2,000 images containing leaves of the wheat plant were collected to develop AI-based model for wheat disease classification, and sample images are shown in Figures 12.2 and 12.3.

Figure 12.2: Healthy leaves.

Figure 12.3: Rust infected leaves.

The author created a dataset of 2,000 images that consist of healthy leaves (1,000 images) and yellow rust infected leaves (1,000 images) (Table 12.1). Hardware specifications used for the experiment are presented in Table 12.2.

These images were captured keeping in mind the different sizes, orientations, and backgrounds. In the case study, Keras and Tensorflow are used as open-source libraries for DL. The graphical processing units facilitate the execution of DL algorithms faster as compared with central processing units. Furthermore, PyCharm is used as the python-integrated development environment for the programming interface. The main objective was to evaluate the model performance for unseen images of yellow rust infected leaves.

Table 12.1: Description of the dataset used.

Image dataset	Wheat yellow rust
Location	ICAR – Indian Agricultural Research Institute, New Delhi
Time period	January to April 2019
Devices used	Canon digital camera, OnePlus 6T phone
Images	2,000
Classes	Two

Table 12.2: Basic hardware specifications.

Hardware and software	Specifications
Operating system	Ubuntu
Processor	Intel Core i7-3930 CPU @ 3.60 GHz
Memory	32 GB
Graphics	NVIDIA GeForce GT 360
Environment	Anaconda with Keras
IDE	PyCharm

These hyperparameters are empirically determined as per the multiple experiments conducted on the author's own image dataset according to the best results obtained for wheat disease identification. Hyperparameters related to CNN in our experiment are presented in Table 12.3.

Table 12.3: Hyperparameters used for the experiment.

Optimization algorithm	RMSProp
Base learning rate	0.01
Weight decay	0.001
Batch size	10
Loss function	BinaryCrossentropy
Activation function	Sigmoid
Epochs	60

As shown in Table 12.3, root mean square propagation (RMSprop) optimizer was used as it learns the appropriate set of weights and biases of the network and minimizes the loss function. Optimizers minimize the cost function by finding the optimized value for weights. In RMSprop, the learning rates get adjusted automatically, and it chooses a different learning rate for each parameter. Besides, other optimizers can be used such as Adam, Adadelta, and stochastic gradient descent (SGD). The base learning rate is a configurable hyperparameter that controls the rate at which the network learns. For example, learning rate of 0.01 means weights in the network are updated (0.01 × estimated error) each time. Weight decay is a type of regularization method that reduces the weight by a small factor to avoid overfitting. Here, binary cross-entropy loss function is used for training binary classifiers. Other concepts of most important hyperparameters in networks are batch size and epochs. Larger batch size leads to faster training and develops a well-generalized model based on the unseen data. However, larger batch size depends on the computational power of the machine, that is, machine would be able to process the large batch of input data without crashing. The smaller batch size makes the learning slower but not less accurate. Therefore, the optimal batch size selected is 20 according to our machine and data (Figure 12.4).

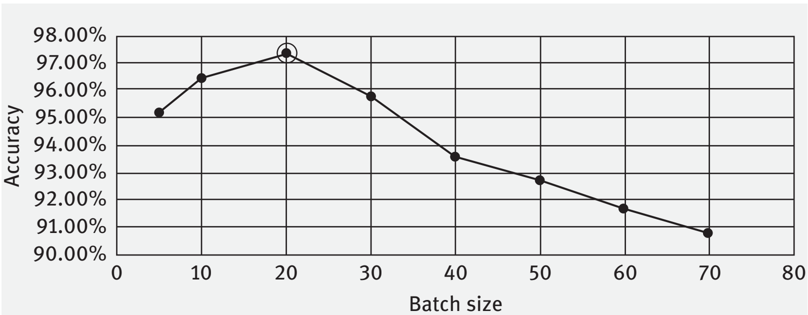

Figure 12.4: Maximum accuracy with a batch size of 20.

The sigmoid activation function performs the nonlinear transformation to the input, which makes it learn and perform more complex features efficiently.

Next, the experiment was conducted by varying the images in a dataset. It is observed that accuracy improves, and time taken for the training also rises as the number of images increases. With maximum available images in the dataset, the accuracy of 97.37% (Table 12.4) was obtained. However, a further increase in accuracy is not ruled out (Figure 12.5).

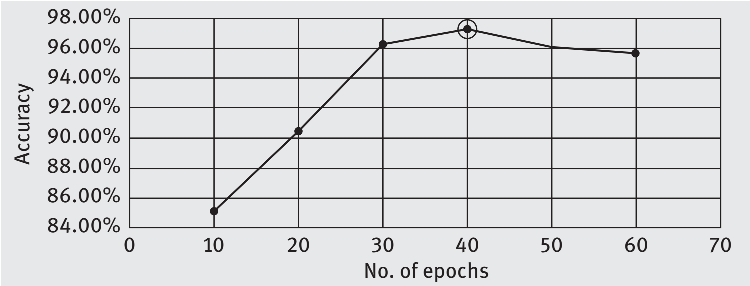

Figure 12.5: Maximum accuracy for epochs size of 40.

Table 12.4: Training time and accuracy varies with the number of images used for training.

No. of images	Time (s/epochs)	Accuracy (%)
100	186	76.0
200	275	77.5
500	394	83.3
1,000	498	90.2
1,500	761	93.6
2,000	1,524	97.37

12.7 Conclusion

DL method shows higher accuracy and uses images directly as input for automatic feature extraction in disease identification. CNN is identified as a suitable and powerful architecture for image-based disease identification. The proposed model achieves 97.37% accuracy, which is quite better than the performance of other models and techniques. The experimental result also reflects that to improve the accuracy, expanding the dataset would help in improving the generalization ability of the developed model. The results presented could be further extended to the development of a mobile application based on wheat disease identification.

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Sandip Kumar Roy and Preeta Sharan

13 Image-based hibiscus plant disease detection using deep learning

Abstract: We have seen plants in our backyard garden get infected with fungal or other insect-borne diseases many times. The early detection and necessary action to prevent plant disease are of utmost importance. Since plants grow in an uncontrolled external surrounding, chances of infection are more. There is a need for detection of the disease-causing insects, the impact of the disease, and how it manifests. The goal of this chapter is to introduce the relevant concepts of plant disease detection. The objective is to explore how image-based plant disease detection technology can provide early detection of plant diseases.

Deep learning uses artificial intelligence (AI), which enables us to interpret the images and show the result with a high probability of success. Deep learning consists of neural networks, hence eliminates the need for dependency of the third party expert. The reason to use deep learning is that it is synonymous with learning, so the system gets enriched as we use the system extensively. Plant disease identification is a labor-intensive process if carried out visually. Manual processes involving this lead to human error and omissions, and can only be applicable on a small scale. However, by using AI-based detection, labor-intensive efforts can be minimized. The technique is time efficient with significantly high accuracy of detection. In leaves, the dark spots, early and late scorch, and others are fungal, viral, and bacterial diseases. For most of the scenarios, there can be a distinct visual change in leaves. Image processing can prove to be handy for identifying, segmenting the disease-affected area, and the impact by measuring the difference in the color of the affected area.

To explain the idea, we have considered case studies for the hibiscus plant disease and insect infection. We have selected hibiscus as there are known diseases that attack healthy, growing hibiscus. Training is the consideration for a deep learning algorithm. The result of training is dependent on the quality and volume of the training data. Case studies presented show high accuracy of 91% for disease detection. Overall, the probability of error is only 9%. The developed algorithm could identify leaves with a defect at a significantly higher rate of 94%. Precision on how often its prediction is correct to the actual condition of the leaves is 92%. The case study result shows that a deep learning algorithm could be a reliable technique for plant disease detection.

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https://doi.org/10.1515/9783110691276-013

Keywords: deep learning, artificial intelligence, image processing, image analysis, plant disease, hibiscus, machine learning, confusion matrix, deep neural network (DNN), deep convolution neural network (DCNN), big data, Internet of things (IoT), smart mobile, cloud-sourced data, rectified linear function (ReLU), sigmoid, vanishing gradient problem. western blotting, reverse transcription polymerase chain reaction (RT-PCR), microarrays, chlorosis, wilting

13.1 Introduction

Plant disease identification based on leaf's morphological inspection is in use extensively. Historically, infectious biogenic elements were fathomed out via visual inspection with the removal of diseased leaves as the next step. The advanced research and implementation of biotechnology led to the development of innovative techniques for plant disease identification. Western blotting, reverse transcription polymerase chain reaction, and microarrays are popular techniques. However, all these techniques require skilled technicians and arrangements for detection. Mostly, these are human labor intensive. The current technology gap is there in terms of popularization and ease of use. The reason for less popularization of this technology is because the cost of adoption is high with a high maintenance cost. Other techniques are investigated because these techniques are destructive and use chemicals. The chemicals used to get rid of plant disease can provide a remedy to the cause but have a harmful effect in the long run for the plant as a whole and the fruits. Consumption of such leaves/fruits poses long-term health hazards. Plant disease identification using image analysis started in 2012. In this work, we have an artificial neural network-based classifier for classification with a recognition rate of up to 91% [1].

There is a growing demand for neural network-based plant disease protection using available images and associated data. A plant disease protection system should comprise the capability of controlling plant diseases. Historically, an artificial neural network is in use for data mining, speech recognition, face detection, driverless car, and computer vision. Recently, growing interest is in using hyperspectral data for early disease inspection [2]. Deep convolution neural network (DCNN) has unique capabilities such as learning, generalization, and imagination to facilitate a reliable diagnosis of plant disease. DCNN promises a higher degree of diagnosis capability than other machine learning algorithms because of the use of the convolution layer concept.

With organic concept getting popular, there is a growing need to avoid chemical-based pesticides for plant disease treatment. The idea of image-based analysis is in use for many other areas of medical research. The objective of the current implementation is to use a similar concept for plant disease detection. While technology intent is good and used definitely to safeguard a healthy life, there are limitations of technology popularization. The challenge with such a technique is that the earlier solutions need to use costly computers. Thus, there is a gap, as current technology is for desktop devices, but the need for the hour is apps running in mobile devices without the use of trained domain experts to interpret the images. The proposed work of deep learning algorithm development is an attempt to reduce the labor-intensive manual process and use of smartphone-based images for analysis.

We structured this chapter into six sections. Section 13.2 presents a brief literature review on image analysis and neural networks for the detection of plant diseases. Section 13.3 covers the materials and methods for plant disease identification. This section presents the introduction of deep learning, image-based detection, and the implementation methodology using deep learning. Section 13.4 discusses the proposed work and sample data considered for the detection of hibiscus plant disease. Section 13.5 describes the result of the use cases for hibiscus plant disease detection using artificial intelligence (AI) technology. Section 13.6 presents the conclusion and future implementations like mobile app-based services. Finally, we conclude with the challenges and drawbacks of the proposed work.

13.2 Literature review

Image processing is an essential component of deep learning-based algorithm implementation. There are various ways of performing image processing, ranging from the simple thresholding method to advanced color image segmentation methods. Furthermore, image processing includes iterative methods for image analysis and restoration [3]. Pooja et al. have presented an innovative approach for plant leaf disease detection using image analysis [4]. The concept behind image analysis lies in mimicking human visual inspection and learning. The detection method used for visual inspection by machine learning uses threshold segmentation [5]. The neural network provides means to intelligently recognize objects, and many different algorithms have been developed to leverage preprocessed images. Study on crop disease diagnosis based on image recognition is carried out in the University of Science and Technology of China [6]. Mokhtar et al. presented a paper about identifying leaf viruses of two tomatoes using a support vector machine [7]. An interesting article associated with plant harvesting used color image segmentation [8]. Cui et al. presented a plant pest detection using an artificial nose system [9]. Some of the recent work involves hyperspectral imaging for plant disease detection [10]. Ahmadi et al. presented a spectral analysis using a neural network [11]. Multiple authors published their work on plant disease detection in a Springer book [12]. Implementation of support vector regression technique to identify components of compound oxytetracycline powder is another interesting work [13].

13.3 Materials and methods

13.3.1 Introduction of deep learning and image-based detection

Deep learning is hierarchical learning based on the representation of data and is a subset of AI. The word deep is used in this type of machine learning implementation because a large number of steps are involved for data processing to get the desired output (Figure 13.1).

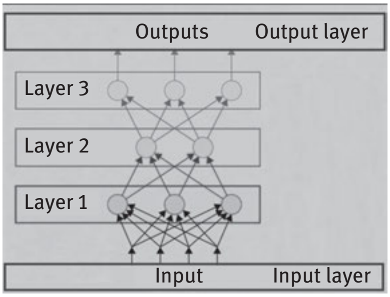

Figure 13.1: Deep learning neural network.

The network of neurons mimicking human brains is the basis of a neural network (Figure 13.1). A neural network is in use for AI. AI architecture consists of the input layer, output layer, and multiple hidden layers in between. In Figure 13.4, layer 1, layer 2, and layer 3 are hidden layers. Deep neural network (DNN) must contain more than one hidden layer. DNN is used to analyze for a specific region of an image rather than analyzing the whole and hence, are more useful for image recognition. The method commonly used for image-based DNN is convolution. In such implementation, the image-based analysis of a specific feature of the image can be done efficiently with accuracy compared to other neural networks. In the case of a large number of input and hidden layers, there might be overfitting or underfitting, and a DCNN is best suited to address this issue. Overfitting refers to the condition where because of the high volume of data, the neural network could not learn. DCNN architecture handles this by introducing three more parameters such as height, width, and depth convolution, pooling, and fully connected layers.

Foundational layers of DCNN consist of pooling, convolutions are stacked in a network to solve multi-class image classification problems. For a DCNN implementation of plant disease detection, the challenge is large-sized images. The developed DCNN needs to be fast and accurate so that it can get trained for a large number of features detection. The approach taken in DCNN is the convolution layer instead of using the fully connected layers.

Various architectures of deep learning including DNN, belief network, and recruitment network are used in areas like computing, audio recognition, language processing, and machine translation, that is, converting machine language into computer language. There are several areas of research in image processing and recognition system. Image processing involves feature extraction, segmentation, and help in object identification. With the advent of the highly sophisticated image capturing devices, algorithms to analyze the captured images of the area of image analysis research is vast. To summarize, the following are the reasons for choosing deep learning in this chapter:

– Deep learning can handle big data. With the convergence of the Internet of things, smart mobile apps, and readily available cloud-sourced data, the developed algorithm needs to cater high volume of data when implemented on a commercial scale.
– The computing power need can be managed by edge computing or by cloud sourcing. Irrespective of the source of the computer system available, the developed algorithm should run. Deep learning algorithm implementation works in a distributed manner.
– Improvisation in the algorithm is possible for deep learning implementation. This capability of deep learning has changed the way neural network works such as using the rectified linear function (ReLU) function is much better than using a sigmoid function in training a neural network, because it helps with the vanishing gradient problem.

DCNN is a promising neural network with the following key consideration while assessing the developed algorithm.

1. It is an iterative learning algorithm and impossible to get all parameters right from the first time.
2. So, the concept revolves around the idea of going through the loop, that is, start with an idea, write code, and then test. Find out the test result and refine the codebase. The algorithm has to go through the loop many times to figure out the right parameters.
3. Do not exhaust all the available data in training. Generally, the dataset is categorized into three parts for optimal results. The training set is 60%, development set is 20%, and the testing set is 20% for a dataset in the range between 100 and 1 million. For dataset greater than 1 million, the training set is 98%, development set is 1%, and testing set is 1%.

The process of algorithm development is shown in Figure 13.5.

As shown in Figure 13.2, model algorithm development is dependent on the training set and how to optimize parameters on the development set as close to the actual as possible. The developed model was evaluated using the testing set.

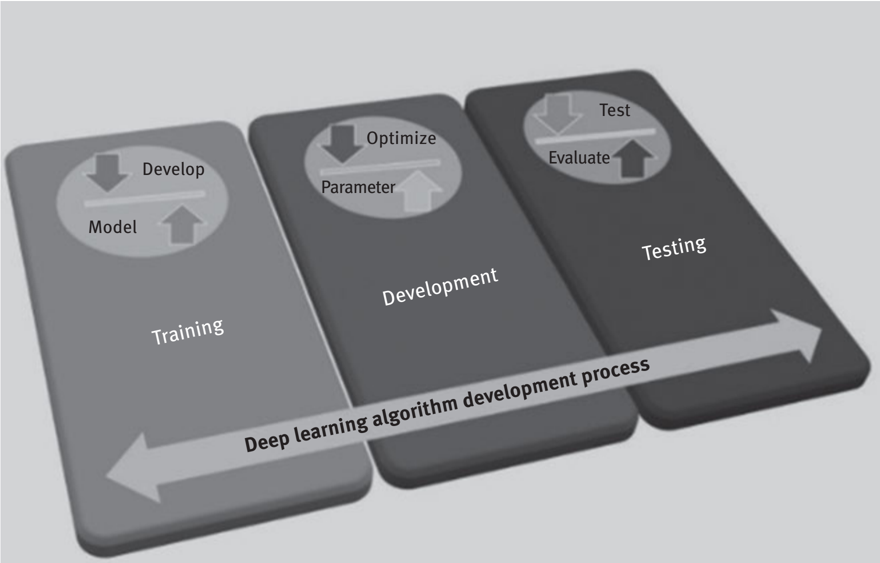

Figure 13.2: Deep learning algorithm process.

1. The training, the development, and the test set should be from the same size and distribution. If, for example, the plant leaves training pictures are from one source, and the development/test pictures are from a different image source, then there will be likely degradation of accuracy of the algorithm.
2. Ensure that the development and test image sets are compatible.

13.3.2 Implementation methodology using deep learning and image-based detection

Figure 13.3 shows the AI algorithm flow chart with essential three stages: image preprocessing, region analysis, and output result. The image preprocessing step is needed to train, validate, and test any AI-based model for computer vision. The input layers contain a preprocessed digital image. With the scalar product between the input layer, weights, and bias, the convolution layer will determine the output. To control overfitting or underfitting, enhance the accuracy of prediction, ReLu is used. Finally, the softmax function is used to get the output. Figure 13.4 shows the steps of the code for the implementation of the DCNN using MATLAB.

During the implementation of deep learning for hibiscus plant disease detection, images are taken form a mobile camera of a smartphone. The sample images were converted into grayscale and another format, segmented and then subsequently classified using a DCNN. The implemented code does the required function to come out with the probability of detection of wilting hibiscus leaves.

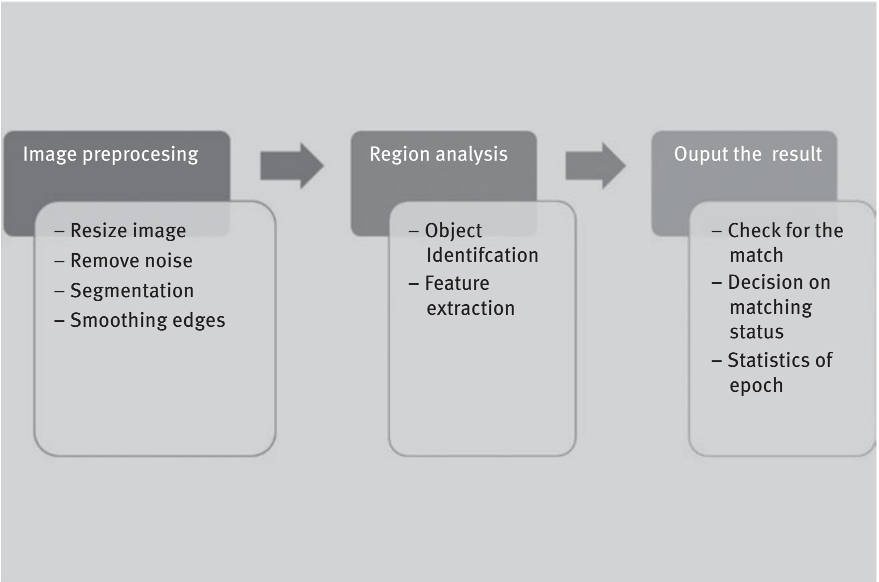

Figure 13.3: AI algorithm implementation flow chart.

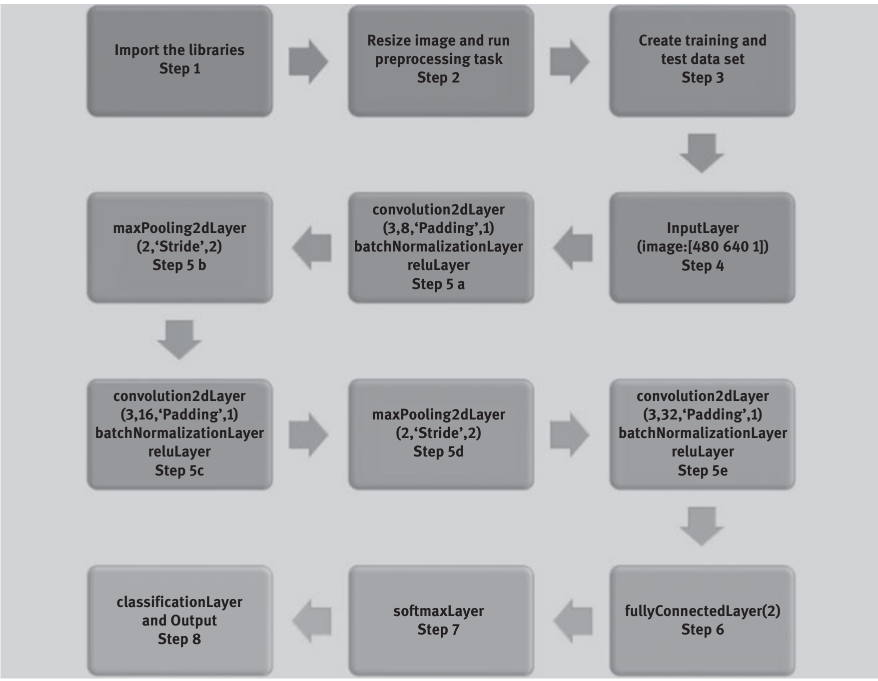

Figure 13.4: Steps for implementation of the deep DCNN.

13.4 Proposed work – hibiscus plant disease detection

Hibiscus is a genus of flowering plants in the mallow family, Malvaceae [14].

(a) (b)

Figure 13.5: (a) Hibiscus flower and (b) normal leaves.

Hibiscus species are renowned for their large, showy flowers and beautiful leaves as in Figure 13.5(a) and (b). Although there are very few diseases that attack healthy, growing hibiscus, it is better to prevent disease before it strikes [15]. The essence of disease prevention is to monitor the growth of the plant regularly. The growth is one of the best preventions of diseases in hibiscus. When a plant gets growing, the immune system also works harder to fight the infections; hence, the hibiscus plant becomes much more capable of protecting itself from any kind of bacterial, fungal, or viral attack. On the contrary, if the plant shows signs of languishing and retarded growth, the immune system also becomes poor, risking the plant for a disease. The fight against diseases requires the hibiscus plant to grow. The early sign of infection in hibiscus is wilting of leaves even though watering is properly done [16]. The first step of identification is to look at the leave's color. If the green leaves starts to turn yellowish, that means, it is showing signs of chlorosis. Other causes of infections are pests, fungi, bacteria, and viruses. Sometimes water in the soil and insufficient sunlight result in growth retardation. Figure 13.6 shows sample images of diseased leaves.

To prevent growth retardation, the early detection of color change as in Figure 13.6(a) is important. In the absence of any preventive measure, the leaf (the powerhouse) of the tree becomes chlorophyll-less as shown in Figure 13.6(b).

Our case study involves the detection of color change at an early stage to alert forthcoming problems with plant growth. This will help the gardener to provide the

Figure 13.6: Sample images of wilting hibiscus leaves: (a) start of symptom and (b) fully wilted.

hibiscus plant with necessary remedies such as proper watering, growth hormones, amino acids, growth enhancer, or a simple rearrangement to get proper sunlight. Sometimes mineral deficiency in soil results in need of extra magnesium and iron.

Our next study involves the detection of insects on leaves as in Figure 13.7 to alert problems with plant growth. This alert will help the gardener to arrange insecticide. Based on the mapping of the identified insect in the database, a proper remedial measure to control insects by the deep learning system is possible. Before we further discuss the methodology used in this case study, we will discuss briefly deep learning and image-based detection technique.

Figure 13.7: Raw image with insect.

13.4.1 Image preprocessing

Since some of the sample images used as input to the DCNN algorithm may vary in dimension, we establish a base dimension for all input images for the developed system. Since background data is irrelevant, using the image segmentation technique, the background data is removed (Steps 1 and 2 of Figure 13.4.). Figure 13.8 shows some of the original samples and corresponding output after image processing. Depending

Figure 13.8: Sample images from training data and resulting processed images.

on the need for DCNN, different preprocessing is taken up. Figure 13.9 shows the result of segmentation on a grayscale image.

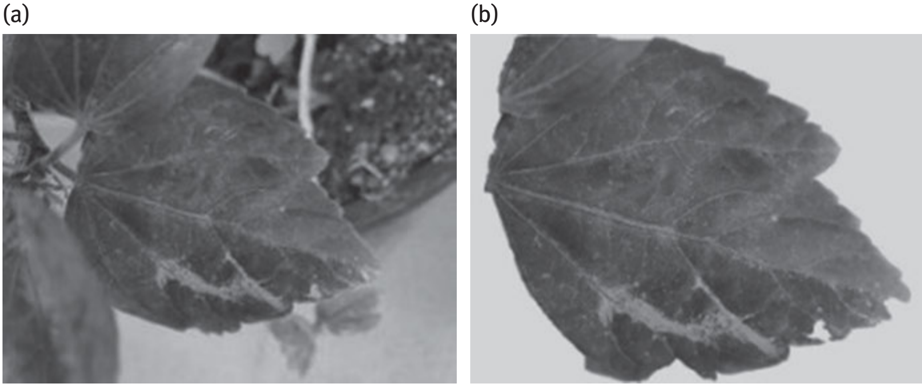

Figure 13.9: (a) original image and (b) segmented image without background.

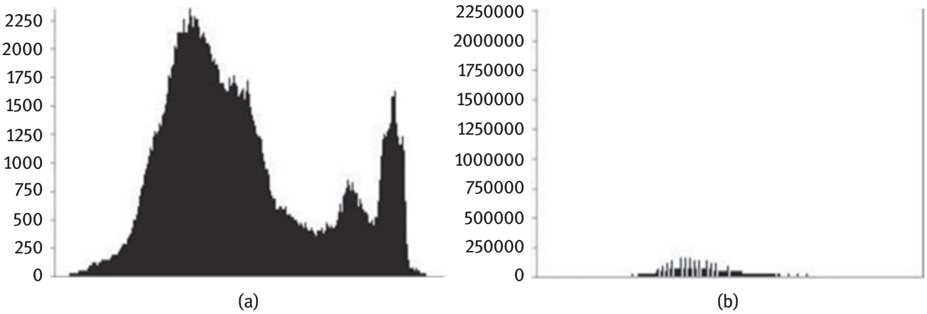

Figure 13.10: Histogram of grayscale sample image before and after segmentation.

We concluded that due to the removal of unwanted background in an image as in Figure 13.10, the distribution is localized between 0 and 254. The targeted DCNN algorithm's efficiency is dependent on segmentation and is very important. There are multiple improvement approaches presented recently [17]. This study is beyond the scope of this chapter; hence, DCNN algorithm implementation is elaborated in the next chapter.

Figure 13.11 shows how image feature extraction and segmentation can help to identify an insect. For the current study, we have considered only a fly, but the same can detect organisms like caterpillar, tiny green, and white or black pests.

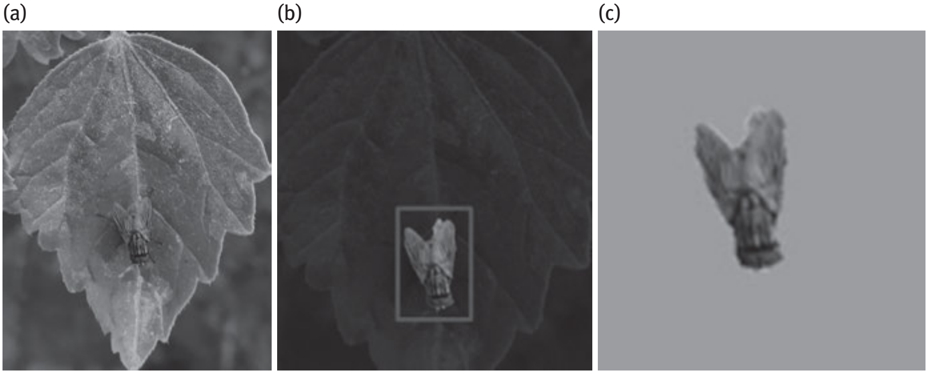

Figure 13.11: (a) Raw image with insect, (b) unique feature identification, and (c) extracted insect.

13.4.2 DCNN algorithm implementation

The next step after image preprocessing is DCNN implementation. Gray images are segregated (similar to the image shown in Figure 13.9) into training sets and test sets. Gray-level preprocessed images are used to avoid large memory requirements for the DCNN processing of colored images from smartphones. For a large number of data, training is performed in epochs. The larger the size of the epoch of data, the more computing capacity is required to obtain high accuracy. Furthermore, to improve the overall accuracy of the trained data, in light of the available computing power of the device, the optimal epoch is finalized. The "convolution2dLayer," "batch normalization layer," and "relayer" (step 5 of Figure 13.4) are used in sequence, with a pooling layer in between. During the implementation, three convolution layer sets are used with an increasing number of filters at each layer within a set.

13.4.3 Classification

After training, the classification of the test set is performed by the DCNN. The output set of layers (steps 6–8 in Figure 13.4) consists of "fullyConnectedLayer," "softmaxLayer," and "classificationLayer" [18]. For more details about steps of implementation, online sources from MathWorks can be referred [19].

To conclude, DCNN progressively extracts high-level features from raw data and preprocessed data. Lower layers extract simple features like boundaries from images whereas higher layers extract distinct features within these boundaries. As mentioned earlier, there are few normalization layers in between as well.

13.5 Result and discussion

13.5.1 Use case for hibiscus plant disease detection

In the previous section, we discussed the methodology used for the DCNN implementation. However, one of the important challenges here is to collect a sample to train the system. Through the Internet and our own effort, we could collect sample images to train the system.

The hardware specification used for hibiscus plant disease detection DCNN is as given in Table 13.1. Also, for image capture, a smart mobile phone camera is used for high-resolution images.

Table 13.1: Hardware specification for the computer.

Component	Specification
CPU	Intel Core i5-8250 U processor (6M Cache, up to 3.40 GHz)
# of Cores/ # of Threads	4/8
Memory	DDR4 2133/2400 MHz，two SO-DIMM slot, support up to 32 GB
System	Windows and Linux supported

Table 13.2 shows the DCNN input and epoch parameters used for running the algorithm.

Table 13.2: DCNN parameters.

S. no.	Specification	Value
1	Sample size for input image	640 × 480
2	Batch size	2
3	Batch normalization: “batchnorm_1”	8 channels
	Batch normalization: “batchnorm_2”	32 channels
4	Weight initialization algorithm	Gloret
5	Learning rate	.01
6	Pooling maxpool_1 'maxpool_2	2 × 2
7	Stride	2
8	Optimization algorithm	Stochastic gradient descent (SGD)

A mapping database is required to map a plant leaf with the origin, where each sample is associated with a plant. When DCNN marks a diseased sample, the system could trace the parent plant. Table 13.3 shows the mapping table.

Table 13.3: Leaf to plant mapping.

S. no.	Plant #	Sample #
1	2019_10_20_01	2019_10_20_01_01
2	2019_10_20_01	2019_10_20_01_02
3	2019_10_20_02	2019_10_20_02_01
4	2019_10_20_03	2019_10_20_03_01

Table 13.4 shows the normal and disease-infected leaves that are used to train DCNN.

Diseased leaf indicates that the associated plant may have retarded growth.

Table 13.4: Sample data classifications for wilting.

No.	Classification	Count
1	Normal leaf	430
2	Diseased leaf	66

To analyze the result, we used a confusion matrix for a two-class classification problem. A confusion matrix is in Figure 13.12. A confusion matrix can evaluate the performance of a classification model (or "classifier") using a set of data with a known result.

TN = 130	FP = 23
FN = 16	TP = 261

Figure 13.12: Confusion matrix for wilting leaves.

As per the confusion matrix “predicted” refers to DCNNs trained algorithm’s assessment of several leaves with the disease. “Actual” refers to the known cases. The parameters true negative (TN), false positive (FP), false negative (FN), and true positive (TP) refer to the standard interpretations [20].

Interpretation of Table 13.5 and Figure 13.13.

- Overall, the DCNN classifier can detect disease with an accuracy of 91%.
- Overall, the detection may go wrong for the rest of the samples up to 9%.
- The developed DCNN’s predictability of actually diseased leaves identification is highest, that is, 94%.

Table 13.5: Actual performance of the DCNN.

S. no.	Performance parameter	Value
1	Accuracy:	91%
2	Error rate:	9%
3	Sensitivity:	94%
4	False positive rate:	15%
5	Specificity	85%
6	Precision:	92%
7	Prevalence:	64%

– The most challenging parameter is the FP rate. Because even though the algorithm identifies the sample true, the reality is negative. Thankfully the implemented DCNN is only 15%. With more and more testing, the algorithm will get further trained.
– This parameter leads to the slippage of the identification of a true normal leaf result. The current implementation is 85%. The rate is impressive, and for 85% of cases, the system will be able to match with the actual state of the leaf.
– The most valued parameter is "precision," as it predicts how often its prediction is correctly mapped to the actual condition of the leaves. The result shows it is 92%, which is significantly accurate, and with more training, this will get further improved.
– The "prevalence" result is 64%, which indicates the samples used are associated with 64% healthy plants.

13.5.2 Use case for detection of insect-infested hibiscus leaves

Furthermore, we extended the work for the use case for the detection of insects on hibiscus leaves.

Table 13.4 shows the normal and pest-infected leaves used to train DCNN.

An insect-infected leaf indicates that the associated plant may have issues in the long run.

To analyze the result, we have used a confusion matrix for a two-class classification problem. A confusion matrix based on sample data with the insect is shown in Figure 13.14.

Interpretation of Table 13.7 and Figure 13.15.

– Overall, the DCNN classifier can detect disease with an accuracy of 92%.
– Overall, the detection may go wrong for the rest of the samples up to 8%.
– The developed DCNN's predictability of actually diseased leaves identification is highest that is. 93%. The sample data classification is presented in Table 13.6.

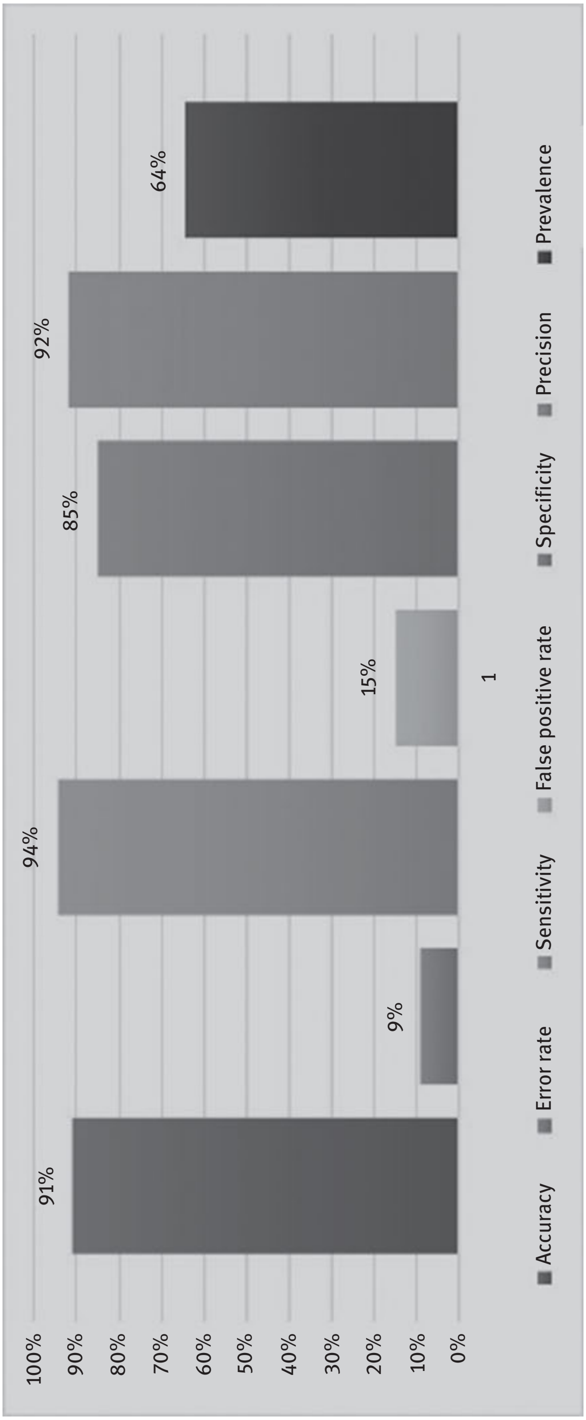

Figure 13.13: Graphical representation of DCNN performance for wilting detection.

Table 13.6: Sample data classifications with insect.

No.	Classification	Count
1	Normal leaf	130
2	Leaf with insect	36

TN = 25	FP = 4
FN = 7	TP = 94

Figure 13.14: Confusion matrix for insect detection.

Table 13.7: Actual performance of the DCNN for insect detection.

S. no.	Performance parameter	Value
1	Accuracy	92%
2	Error rate	8%
3	Sensitivity	93%
4	False positive rate	14%
5	Specificity	86%
6	Precision	96%
7	Prevalence	78%

– The most difficult parameter is the FP rate. This is, because even though the algorithm is identified as true, it is negative. Thankfully the implemented DCNN is only 14%. With more and more samples, the algorithm will get further trained. This is likely to go down.
– This parameter leads to the slippage of identification of leaf without insects. In the current implementation, this is 86%. The rate is impressive and for 86% of cases, the system will be able to match correctly with the actual state of the leaf.
– The most valued parameter is “precision,” as it predicts how often its prediction is correctly mapped to the actual condition of the leaves. The result shows it is 96%, which is significantly accurate, and with more training, this will get further improved.
– The “prevalence” result is 78%, which indicates that the samples used are associated with 78% of plants without any insect.

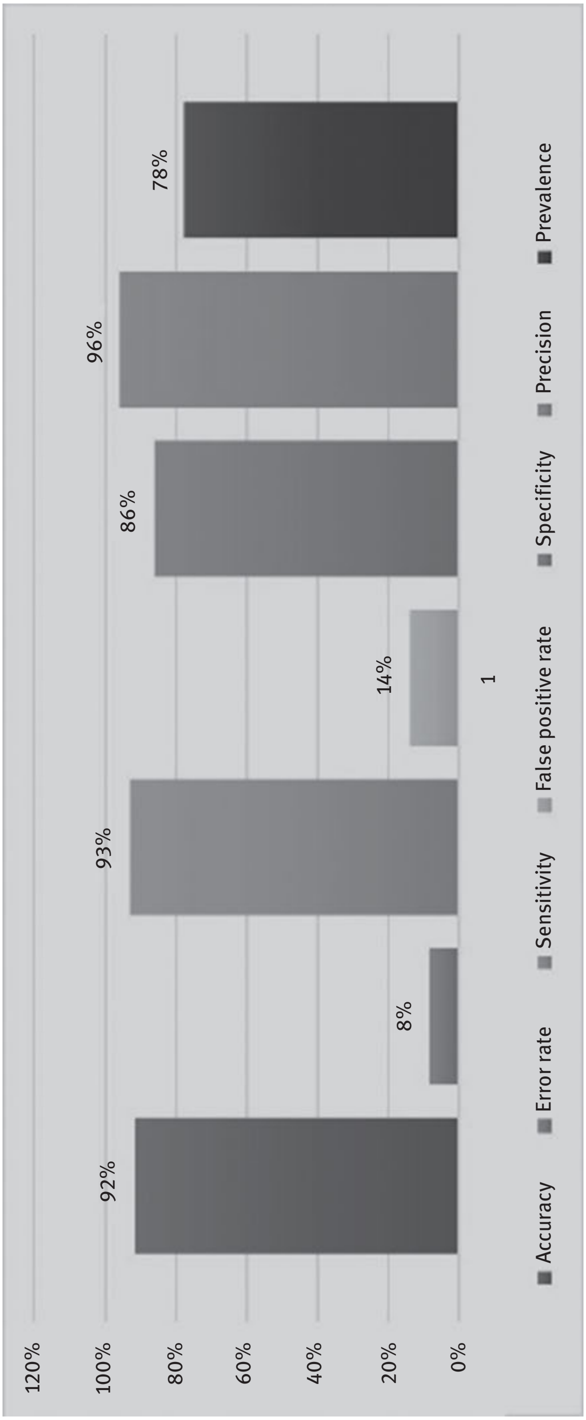

Figure 13.15: Graphical representation of DCNN performance.

13.6 Conclusion

Our objective of the case study was to exceed the artificial neural network-based classifier recognition accuracy rate of up to 91% [1]. In both the case studies, the accuracy achieved was greater than 91%.

Table 13.8 shows the comparison of wilting versus insect detection using DCNN:

Table 13.8: Comparison of result: wilting versus insect detection using DCNN.

Parameter	Wilting leaves	Leaves with insect
Accuracy	91%	92%
Error rate	9%	8%
Sensitivity	94%	93%
False positive rate	15%	14%
Specificity	85%	86%
Precision	92%	96%
Prevalence	64%	78%

- Most of the parameters of the DCNN classifier are within 1% variation between the two case studies – wilting leaves and leaves with insect.
- The most valued parameter is "precision," as it predicts how often its prediction is correctly mapped to the actual condition on the leaves. The result shows it is 96% in the case of insects, whereas for wilting it is 92%. The reason is that the segmentation and feature extraction are more accurate in the case of insects.
- The "prevalence" is 78% in the case of insect, whereas for wilting it is 64%. The reason is that the source distribution actually has fewer insects.

Figure 13.16 shows the graphical representation of wilting leaves versus leaves with insect detection using the DCNN for plant diseases.

In the context of plant disease detection using a deep learning algorithm, DCNN model can be developed by finalizing the neurons, their convolution relation, and outputs. A multilayer DCNN, which is the most dynamic and widely used, is implemented for plant disease detection. The output result has shown a great possibility of the use of the concept. The concept can be further extended for many future applications like insect detection and remedial mobile application for farmers.

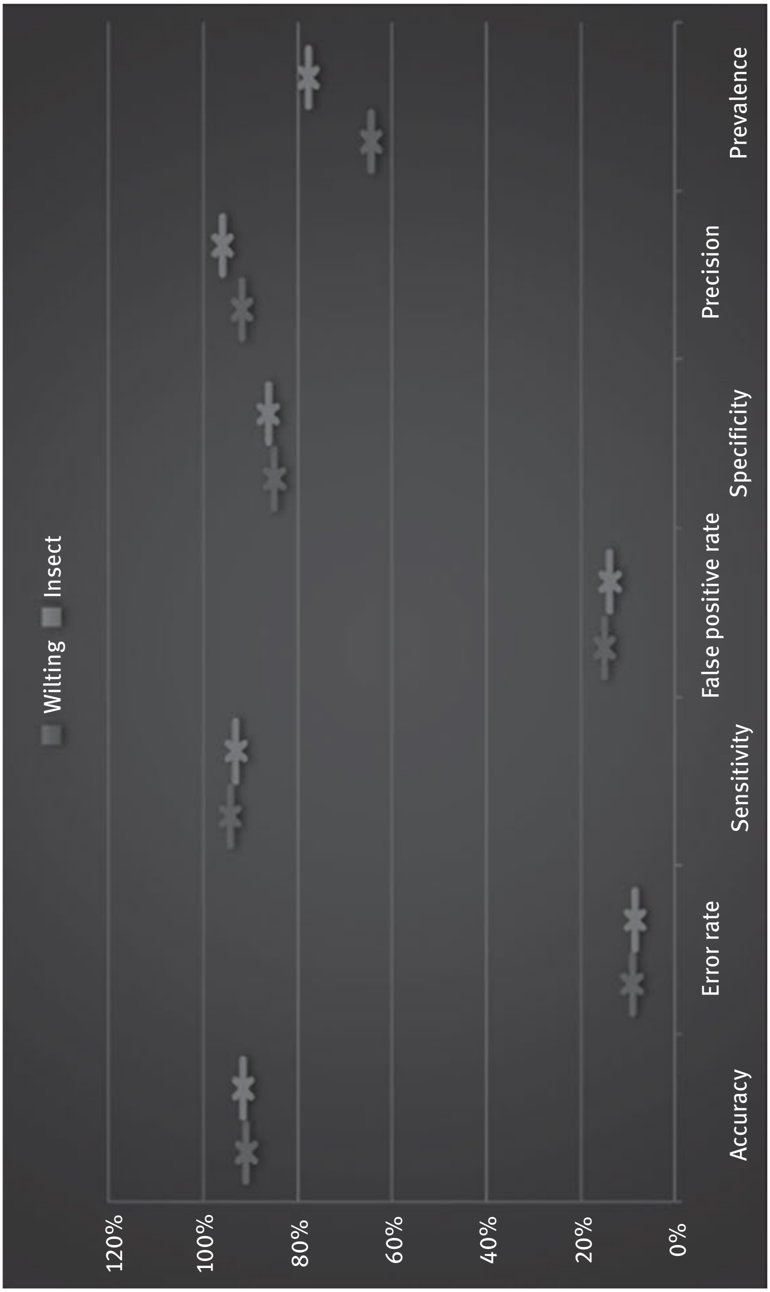

Figure 13.16: Comparison of two case studies: wilting versus insect identification.

13.6.1 Future applications

Future use cases will be based on deep learning's capability to provide cost-effective detection. The segmented images in Figure 13.17 shows how, while using DCNN, an insect on a leaf can be identified.

Figure 13.17: Insect identification using DCNN.

Using commonly used insect databases, DCNN algorithms as presented in this chapter, the segregated insect image can be used to identify an insect on a leaf. The presented technology shows how disease attacks can be prevented. How a particular geographical area can further be alerted about the spread of disease or insects can be some of the future applications using deep learning.

Furthermore, the proposed deep learning system when fed with a leaf image, will be capable of detecting the diseases, insects stored in the developed system's training database to provide information for bioinformatics dashboards.

Finally, the aim of image-based deep learning algorithm presented in this chapter is not to find an alternate solution for the existing techniques for plant disease diagnosis. The idea behind experimenting with the new approach is to supplement the existing techniques. With the device-level research using AI of image capturing on mobile, the highly accurate diagnoses via the smartphone are future for plant disease diagnosis.

13.6.2 Challenges and drawbacks

A typical deep learning implementation involves training the system with real-world data. Most of the time, the images in detection require preprocessing to reduce the processing time and detection error. Therefore, the result depends on the image quality and the preprocessing applications. Some of the drawbacks of image preprocessing are as follows:
– The obtained accuracy of implementation is in the range of 91–94%, hence, need further optimization.
– For segmentation, knowledge about the plant type, prevalent diseases, and available source and distribution should be available.
– A large number of sample images are required to segregate training, development, and test data.
– In this study, few diseases and insect identification are covered.
– The 6–9% misclassifications in relation to disease symptoms vary from one plant to another, insect feature optimization is needed for more training images to train the DCNN to cover more cases, and to predict the disease more accurately.

Another challenge is to get the right quality of images in rural areas, where costly mobile devices with high resolution are not commonly available. The major challenge is to implement a concept that is independent of the expert's validation and dependent on decentralized images. Deep learning brings a high degree of training dependency challenges to remain for effective implementation by farmers. However, eventually going forward, these limitations will be overcome, paving the way for many new use cases.

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Mahua Bose and Kalyani Mali

14 Rainfall prediction by applying machine learning technique

Abstract: Rainfall forecast significantly affects the country's economy. It also helps in reducing the loss of life and property caused by natural disasters. This chapter presents a review of the research works in rainfall forecasting using machine learning techniques with special emphasis on India. In India, about 70% of the people depend on agriculture and related works. Prediction of rainfall is a matter of great technical and economic importance in the agricultural industry. In this chapter, we have highlighted techniques that appeared in the IEEE Xplore, ScienceDirect, and SpringerLink in the last 10 years.

Keywords: agriculture, artificial neural networks, ensemble, fuzzy

14.1 Introduction

Rainfall forecasting is a complex technique that is dependent on a lot of parameters. Variability of rainfall over different seasons influences agriculture, irrigation, vegetation, and soil characteristics. Advance knowledge about fluctuations in the rainfall is necessary to reduce the loss caused by flood, drought, or cyclonic storm. Forecasting significantly affects decision-making in the field of finance, ecology, atmospheric science, agriculture, forestry, and so on.

The forecast can be long term, short term, or midterm depending upon the duration of the forecast. In addition to that, the forecast can be made using terms like heavy, moderate, or light rainfall. Information about different weather elements is obtained from various sources (Figure 14.1). The description of the different seasons in India is shown in Table 14.1.

The objective of this chapter is to prepare a survey of rainfall prediction techniques using machine learning techniques. Section 4.2 discusses the need for rainfall prediction. The reviewed works will be categorized according to the technique used in Section 14.3. The prediction periods are arranged daily, monthly, and yearly (Table 14.2). In addition to that, we will list the variables used in multivariate models (Table 14.3). We will also provide the performance evaluation techniques used

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https://doi.org/10.1515/9783110691276-014

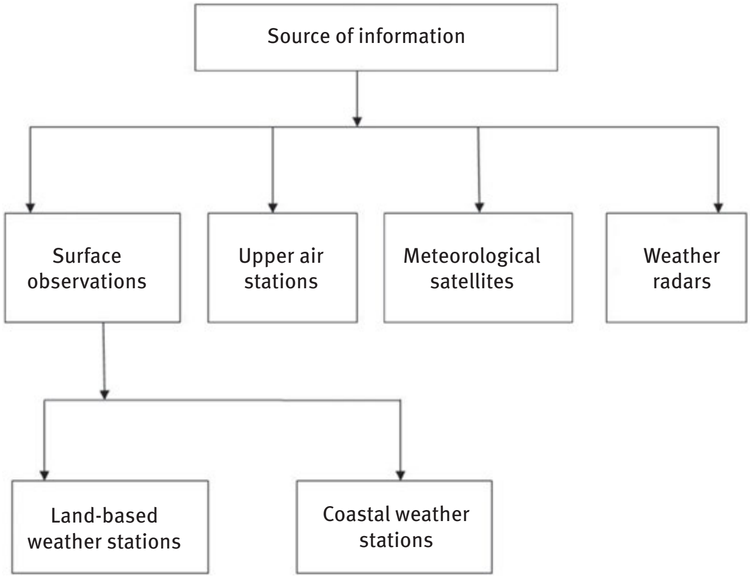

Figure 14.1: Collection of weather elements.

in these models (Table 14.4). In Table 14.5, terms used in this chapter are provided. Finally, the conclusion is given in Section 14.4.

14.2 Need for predicting rainfall in India

India receives rainfall mainly due to southwest monsoon every year. Southern part of India (east coastal region of Andhra Pradesh and Tamil Nadu) receives rainfall in winter season also. Rainfall has great impact on food grain production. Karif season (June–September) is directly dependent on day-to-day variation of summer rainfall. Increase/decrease in rainfall is related to the increase/decrease of food grain yield. Summer rainfall indirectly affects the rabi crop (winter season) by providing soil moisture and irrigation facility. Drought in summer causes reduction in food grain production. On the other hand, excessive rainfall affects crop growth due to various crop diseases [1].

14.3 Categorization of techniques

14.3.1 Models based on single prediction system

Models applying a particular machine learning technique [2, 3] or hybrid models where forecasts are obtained using a single prediction system will be discussed in this section. Here, models are categorized according to the techniques applied. Ensemble [4] based models will be discussed in the next section.

Artificial neural networks (ANN) are modeled after human nervous system [5]. Network has an input layer (where input patterns are fed into the system) and an output layer (produces outcome of the input). In the network, one or more hidden layers may be present. There are several variations of this network.

(1) The feed-forward neural network (NN) has been widely used by researchers in rainfall forecasting. Backpropagation (BP) is a supervised learning method used in feed-forward networks [6]. Application of multilayer perceptron (MLP) NN is also observed for the prediction of week-ahead rainfall [7]. Feed-forward BP NN algorithm using five NN architectures [8] has been used for Indian summer monsoon rainfall (ISMR) forecasting. For the purpose of ISMR forecast, it is revealed that regularized online sequential network (random vector functional link network (RVFL)) model [9] outperforms feed-forward NN and RVFL. Monsoon and post-monsoon rainfall in Kerala are predicted using different models like *K*-nearest neighbor (KNN), ANN, and extreme learning machine [10]. Prediction performance of the hybrid model [11] integrating backpropagated neural network (BPNN) and random optimization is also encouraging.

    Modular NN is a collection of several small networks that work together to accomplish a task. The performance of modular artificial NN [12] is best in comparison to three other models using ANN, KNN, and linear regression. The study [13] applies modular modeling methods for rainfall prediction. To improve the accuracy, a data preprocessing procedures such as Moving Average (MA) and singular spectrum analysis (SSA) were carried out first. Results showed that the MA with ANN produces better results than that of SSA with ANN. A study [14] investigating the usefulness of ANN in monsoon rainfall prediction using large-scale climate teleconnections is introduced. A novel BPNN model [15] is also discussed that selects input vectors by stepwise regression and uses Bayesian regularization method. A case study has been prepared [16] in Indonesia using BPNN. A novel extreme rainfall prediction model [17] based on BPNN using the clustering method has been developed. The model takes the impact of discrimination error into account. Immune evolutionary algorithm [18] based on BPNN shows higher accuracy and better stability than BP network algorithm model. A multilayered (three) ANN [19] with learning by BP algorithm has been discussed. BPANN based on Matlab platform [20] is used to achieve better accuracy than regression model. A deterministic and probabilistic ANN model [21] predicted the long-

range monsoon rainfall efficiently. FS (Free search)-BP model [22] is proved to be more stable and accurate than BP model.
(2) Radial basis functions (RBF) [23] are powerful techniques for interpolation in multidimensional space. Application of generalized regression NN model [24] has more advantages in prediction compared with BPNN and stepwise regression analysis methods. A model [25] using empirical mode decomposition together with RBF NN shows high accuracy in denoising and prediction of the rainfall sequence. A hybrid neural model [26] combining MLP and RBF is designed to enhance the accuracy of weather forecasting. The hybrid neural model shows best forecasting accuracy as compared to both of the individual networks.
(3) Learning vector quantization [27] technique integrated with BPNN showed good performance in rainfall prediction [28].
(4) Time-delay NN (TDNN) [29] is an NN architecture that works on sequential data. A focused TDNN [30] has been applied successfully for monthly and annual rainfall prediction in Malaysia. Another time lag NN model [31] is proposed for forecasting monsoon rainfall based on the Indian Ocean dipole (IOD) parameter. It is found that using TDNN [32], the second-order algorithm (Lavenberg–Marquardt) produces better description and forecast of rainfall than the first-order algorithm. Among the other notable works, models using recurrent architecture [33–35] can be mentioned.
(5) A multivariate model [36] using Bayesian approach has been used for rainfall prediction. Another algorithm using a Bayesian method that adjusts parameters for cumulative rainfall time-series forecasting is implemented with an ANN filter [37]. A novel hybrid method of ANN and collective learning automata (CLA) (ANN–CLA) proved to be more efficient than FFBP–Lavenberg–Marquardt and Feed Forward Back Propagation (FFBP) Broyden–Fletcher–Goldfarb–Shanno (BFGS) in predicting rainy days [38]. Applications of various data mining techniques have been observed [39]. In recent years, wavelet techniques, one of the most popular time–frequency transformations, have been applied to find an alternative method for rainfall forecasting. Models based on ANN and wavelet decomposition [40], combined discrete wavelet transform and linear regression [41], and wavelet technique with NN [42, 43] are proposed. Fuzzy set theory [44, 45] captures the vagueness and uncertainty involved in the information. Modular fuzzy inference system [46, 47] is applied to predict rainfall. Multivariate model [48, 49] using fuzzy inference system is also employed.

Adaptive neurofuzzy system (ANFIS) has also been applied in rainfall prediction [50]. A modified version of ANFIS [51] has better forecasting accuracy and lower computational complexity than the conventional ANFIS model. Neofuzzy neuron model [52] for seasonal rainfall forecasting showed a better performance, between predicted and actual output, when compared with a dynamic downscaling model using the regional spectral model.

A new area called fuzzy time-series modeling has major contribution to rainfall prediction [53, 54].

Support vector machines [55] were used as an alternative model to ANN by many researchers. Model using discrete wavelet transform and support vector machine (SVM) [56] is presented for rainfall forecasting.

Among the various optimization techniques, application using particle swarm optimization (PSO) [57] has significant contribution to this field. A comparative study [58] has shown improved performance of PSO– support vector regressions (SVR) over the BPNN and autoregressive integrated moving average (ARIMA) models. A novel hybrid model with evolutionary algorithm called SVR–PSO–SA (Simulated Annealing) [59] is proposed. A comparative study shows that PSO–NN model performs better than the standard BP, BP with momentum, quick propagation, and genetic algorithm with NN models [60] in Malaysian rainfall prediction.

Genetic learning method is a kind of evolutionary algorithm that resolves a task by applying three operations: crossover, inversion, and mutation [61]. Genetic programming [62] has been employed to model the relationship between the rainfall and atmospheric circulation pattern indices such as El Nino–Southern Oscillation (ENSO) and Equatorial Indian Ocean Oscillation. Wrapper-based genetic feature selection [63] is also introduced. Genetic algorithm-based hybrid PSOGA–NN (Particle Swarm Optimization Genetic Algorithm) [64] model combining PSO and NN has been investigated. An evolving RBFNN model is presented for rainfall prediction where hybrid PSO and genetic algorithm are used for estimating parameters of the network [65].

Tree-based models also have contribution in this field. Decision trees are one of the most popular structures (top to bottom) for storing knowledge of classification and prediction. Decision trees can process both categorical and numerical data. C4.5 is an improvement over ID3 [66]. It uses gain ratio criterion to select an attribute. *k*-means clustering technique-based model [67] coupled with classification and regression tree (CART) is used for generation of rainfall states from large-scale atmospheric variables. A prediction model [68] applying CART and C4.5 is also discussed. Decision tree algorithm using Gini Index [69] is also presented.

There are some notable research works [70–76] utilizing radar/satellite information as well. A multivariate forecasting model [77] using MLP with three layers decision tree, J48, and KNN, has shown good results. Multimodel canonical correlation analysis [78], simple Poisson–gamma model [79], MM5 model [80], matrix decomposition [81], imbalanced classification techniques [82], and statistical downscaling approach [83] have shown good results.

In order to determine the occurrence of droughts and related issues, an NN-based model is presented using the standardized precipitation index [84]. Water Reclamation Facility (WRF) model [85] captures the high intensity of rain bands. An ANN-based prediction model [86] is developed (for Nile Basin) based on the information of global sea surface temperature. Model predicting cumulative distribution function of rain rate ($P(R)$) is presented [87]. Lavergnat-Golé models [88] showed good performance using yearly and monthly data. A regional seasonal forecasting system [89] using ENSO and IOD climate mode to enhance management of risks and opportunities in rain-fed agriculture is also presented. In addition, redundancy reduction technique using combination of supervised and unsupervised learning is presented [90]. Works are also carried out to improve the accuracy of the rainfall rate prediction [91, 92].

Models have also been developed combining classical time-series theory with soft computing techniques. Autoregressive NN model [93] combines the autoregression model with NNs. Comparative study [94] on monsoon prediction in Nilgiri district shows that forecasting capability of nonlinear autoregressive exogenous network model is superior to some of the BPNN-based models.

14.3.2 Ensemble-based models

Ensemble learning process [4] combines the outputs of multiple learning machines and produces final prediction as a collective decision taken by these processes. Ensemble models generally show higher accuracy than single models.

Ensemble generation can be called homogeneous if each base model uses same learning algorithm and is heterogeneous if base models are trained by different methods. Ensemble learning process can be divided into three phases: ensemble generation, ensemble pruning, and ensemble integration. Some authors describe ensemble learning process in two steps: ensemble generation and ensemble integration. In the first step, base models are generated, and in the second step, base model predictions are combined to improve results. There exist numerous methods for model combination: linear combiner, product combiner, and voting combiner. First two combiners are applicable when real-valued numbers are obtained as output, whereas the last one is used when models output class labels.

One of the recent works on ensemble methods, particularly in the area of rainfall forecasting, is linear and nonlinear regression-based least-square support vector machine (LS-SVM) ensemble [95]. Here, projection pursuit and PSO are used to obtain main factors of rainfall. To extract linear and nonlinear features, linear regression and NN are employed successfully. Finally, LS-SVM is used as an nonlinear ensemble model. Weight-based multimodel ensemble [96] is also investigated.

Table 14.1: Seasons in India categorized by IMD.

Name	Range
Summer or pre-monsoon	March–May
Rainy or monsoon	June–September
Autumn or post-monsoon	October–November
Winter	December–February

Table 14.2: Duration of forecast.

Duration of prediction	Examples (papers)
Hourly	[68, 71, 73, 77, 80]
Daily	[13, 38, 40, 57, 67, 71, 92, 94, 95, 100–104]
Monthly	[13, 18, 30–33, 41–43, 46, 47, 58, 62, 64, 88, 97, 98, 105–108]
Yearly	[15, 17, 22, 24, 30, 87, 88, 91, 107]

A nonlinear ensemble model employing PSO and NNs has been proposed [97]. Forecast accuracy of ANFIS–ARIMA model [98] is better than the individual ARIMA and ANFIS models. In order to forecast the southwest monsoon rainfall of Kerala, ensemble model combining empirical mode decomposition (EEMD), ANN, and multiple linear regression (MLR) is presented [99].

Table 14.3: Multivariate models.

Multivariate models	Variables used
[77]	Ten attributes are used as predictors
[76]	SST indices
[33]	Climate indices and temperature
[48]	Five variables as predictors
[62]	Using ENSO and EQUINOO
[36]	Seven attributes are used as predictors
[67]	Large-scale atmospheric variables
[104]	Six variables as predictors
[108]	Ten variables as predictors
[111]	Six variables used
[105]	Three variables used
[107, 112]	Convective and total rain amounts

Ensembled continuous Bayesian networks [109] and spatial–temporal covariance model [100] have been introduced. A novel hybrid multimodel approach [100] is proposed for daily rainfall forecasting. A multimodel technique [105] using different regression and NN models is also developed. A bivariate probability distribution [110] based ensemble scheme using single-valued quantitative precipitation forecasts has also been presented.

A novel modular-type SVM is presented [106] to simulate rainfall prediction. First step makes use of bagging sampling techniques to generate different training sets. Second step uses various kernel functions with different parameters on

Table 14.4: Commonly used performance evaluation measures.

Error estimation techniques	Papers (examples)
RMSE	[12, 13, 26, 33, 38, 40, 42, 51, 59, 91, 98, 100, 102, 113]
NMSE	[58, 100, 102, 104, 108]
MAPE	[30, 58, 108]
SMAPE	[100]
Correlation coefficient (CC)	[26, 42, 62, 80, 94, 100, 102, 105]
MAE	[7, 59, 80]
MSE	[16, 94]
Pearson's relative coefficient (PRC)	[104, 108]
Persistent index (PI)	[13, 100]
Coefficient of efficiency	[42, 100]
Bias	[91, 100]
Nash–Sutcliffe model efficiency coefficient (NS)	[13, 102]
Willmott's index	[13]
Brier score (BS)	[48]
Fraction skill score (FSS)	[48]
Hanssen–Kuipers (HK) score	[80]
Percentage (%)	[68, 69, 77]
Scatter index	[26]

Table 14.5: Abbreviations used in this chapter.

ANN	Artificial neural networks
ANFIS	Adaptive neurofuzzy inference system
ARIMA	Autoregressive integrated moving average
ARNN	Autoregressive neural network
BART	Bayesian additive regression trees
BPNN	Backpropagated neural networks
CART	Classification and regression tree
CLA	Collective learning automata
ENSO	El Nino Southern Oscillation
EQUINOO	Equatorial Indian Ocean Oscillation
GP	Genetic programming
GRNN	General regression neural network
IOD	Indian Ocean dipole
ISMR	Indian summer monsoon rainfall
KNN	*K*-Nearest neighbors
K–PLSR	Kernel partial least squares regression
LM	Lavenberg–Marquardt
LS-SVM	Least-square support vector machine

Table 14.5 (continued)

ANN	Artificial neural networks
MANN	Modular artificial neural network
MLP	Multilayer perceptron
MLR	Multiple linear regressions
PCA	Principal component analysis
PSO	Particle swarm optimization
PLS	Partial least squares
QPE	Quantitative precipitation estimates
QPF	Quantitative precipitation forecasts
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MSE	Mean square error
NARX	Nonlinear autoregressive network with exogenous inputs
NMSE	Normalized mean square error
NWP	Numerical weather prediction
RBF	Radial basis function
RMSE	Root mean square error
SMAPE	Structured mean absolute percentage error
SSA	Singular spectrum analysis
SST	Sea surface temperature
SVM	Support vector machine
SVR	Support vector regressions
WSVR	Wavelet support vector machine regression

training sets. Third step applies partial least squares (PLS) technology to choose the appropriate number of SVR combination members. In the final step, a value-Support Vector Machine (v-SVM) is developed by learning from all base models. Recently, an ensemble scheme utilizing SVM [112] has been successfully implemented.

A multimodel ensemble from eight individual prediction systems shows improvement over the single system [114] while predicting Indian monsoon rainfall. A probabilistic precipitation forecasting model [115] using generalized additive models and Bayesian model averaging was presented. Rainfall forecasting based on EEMD is also presented [116]. Two nonlinear ensembles [117] using regression tree and bagged decision tree are presented for the purpose of dimensionality reduction.

Forecasting model for advanced research for prediction of stratiform precipitation events [113] has been presented. The perturbation extraction and inflation method [118] improved the accuracy of forecasts of rainfall and near-surface variables. The ensemble reordering method [101] is capable of producing seasonal forecasts. A unified model [107] for the prediction of high-resolution rainfall rate statistics is also developed. Lyapunov exponent [119], false neighbor algorithm [102], and correlation dimension [103] methods are applied on daily rainfall data of three different regions [111].

Other notable achievements in this field are multivariate nonlinear ensemble prediction using principal component analysis (PCA) technique [120], nonparametric regression ensemble based on PSO and ANN [121], and ensemble scheme based on MLR and the Bayesian technique [122]. Comparison between different ensemble methods is also made by researchers [123].

Studies using RBF NN-based ensembles are also attempted [104, 108, 124–126]. Semiparametric regression combined with PLS has been used to develop a new ensemble [104]. Another new approach [124] using a modular RBF NN technique has been presented. This model makes use of the data preprocessing techniques (SSA) and PLS regression. A novel hybrid RBF–NN [108] ensemble employing Kernel partial least squares regression has been attempted. Another RBF–NN ensemble [125] model using PLS and WSVR is presented for rainfall forecasting. In the BART ensemble model [126], different linear regression models and NN models are applied to extract the linear and nonlinear characteristics of rainfall system, respectively. Application of deep learning technique is also observed [127, 128].

14.4 Conclusion

This chapter surveys recent literature in the domain of rainfall forecasting techniques. Indian economy is mainly dependent on agriculture. Necessity of rainwater for the crops grown in different parts of India varies. Accurate and timely forecast of rainfall has great importance in crop production. The aim of this survey is to present an overview of machine learning techniques used in recent times for the rainfall prediction. We have surveyed many papers employing various algorithms. We observed not only an increasing trend in the research of area of rainfall prediction but also application of machine learning techniques in comparison to statistical methods. ANN has been used in most of the applications. Root mean square error has been applied for evaluating performance of the models in most of the cases. Due to large volume of works carried out in this area, we have included only limited number of papers in this chapter.

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Tan Pham Nhat and Son Vu Truong Dao

15 Plant leaf disease classification based on feature selection and deep neural network

Abstract: Today, deep learning (DL) has transformed many major industries. Agriculture is one such field where DL scientists and researchers are working with farmers to help them utilize the shrinking resources due to urbanization. However, plant disease, especially crop plants, is a major threat to the global food security. Many types of disease directly affect the quality of the fruits, grains, and so on leading to the decrease of agricultural productivity. The conventional method of identifying plant disease is through direct observation by naked eyes. This process is unreliable and subjected to human errors. In recent years, several works on DL techniques for leaf disease identification have been proposed. Most of them built their models based on limited resolution images on convolutional neural networks (CNNs). In this chapter, we want to focus on early disease recognition, which requires higher resolution images. After a preprocessing step using a contrast enhancement method, all the diseased blobs are segmented for the whole dataset. A list of several measurement-based features that represents the blobs are selected based on principle component analysis. The features are used as inputs for a standard feed-forward neural network. Our results show competitive classification results not only with other DL models such as CNNs but also with a simpler network structure.

Keywords: neural network, image classification, plant pathology, feature selection, precision agriculture

15.1 Introduction

The plant diseases are the main cause of losses of agricultural production. However, tools for quick and accurate recognition remain scarce. In addition, there was a significant increase in the spread of pests and diseases recently. The effects of globalization, global trading, and climate changes, coupled with the reduction in the resilience in production systems due to decades of agricultural intensification, have contributed to this issue. Such types of disease can easily spread out of the borders to several countries and become epidemics. The welfares and livelihoods of farmers as well as the food supply and the nutrition security of a nation is severely threatened should any kinds of disease outbreaks happen.

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https://doi.org/10.1515/9783110691276-015

Traditionally, farmers use their eyes to detect diseases and make decisions based on their experiences, which is often not accurate and sometimes biased since in the early stage, some diseases appear to be the same. In addition, their experiences need to be passed down generations by generations. Based on these evidences, the need for an accurate disease detector associated with a reliable database to help farmers is necessary, especially for the case of young and inexperienced ones. Advances in computer vision pave the way for this with the state-of-the-art deep learning (DL) or machine learning (ML) algorithms. There is also a need for an early diseases detection system to protect the crop in time.

There are many previous researches conducted for this purpose. Most of them make use of the so-called PlantVillage dataset, a widely known dataset that is available online, but this dataset is limited in terms of training samples in each category. Also, their approaches are convolutional neural network (CNN), which consumes a large amount of time and memory to train.

15.2 Literature review

15.2.1 Plant diseases recognition using CNNs

CNNs are a class of hierarchical model where object's features are learned by training through many examples. CNNs consist of multiple layers with later ones built on top of previously learned features [1]. Saleem et al. [2] conducted a review on plant disease detection and classification by DL models. Konstantinos et al. [3] implemented a Visual Geometry Group (VGG) model for plant disease detection in which the VGG network achieved 99.53% of accuracy over the "PlantVillage" dataset. Rangarajan et al. [4] used AlexNet and VGG16 to classify tomato leaf diseases in which VGG16 reached 97.29% and AlexNet reached 97.49% of accuracy. Previous works used the "PlantVillage" [5] dataset, which has simple or plain backgrounds, and the sample size in each category is limited, resulting in high chance of overfitting. A much wider variety of training data should be collected from several sources of different geographic areas, cultivation conditions, and image capturing modes. Mohanty et al. [6] implemented transfer learning (TL) with a pretrained AlexNet to classify diseases in crops. Too et al. [7] reviewed DL models namely VGG, ResNet, Inception V4, and DenseNet in disease classification using the "PlantVillage" dataset. VGG16 was also used in Shijie et al. [8] to classify tomato diseases.

15.2.2 Plant diseases recognition with artificial neural network

Khirade et al. [9] conducted a review on different types of approaches to segment the infested plant parts. This research also reviewed some methods to extract the features from damaged leaves and classify the types of disease. There are many approaches using artificial neural network (ANN) networks for the same problem such as self-organizing feature map, backpropagation algorithm, and support vector machines (SVMs). Singh et al. [10] used ANN together with image segmentation to detect diseases on various types of plants, namely, banana, beans, jackfruit, lemon, mango, potato, tomato, and sabota. The processing step is first done using the minimum distance criterion with *k*-means clustering. In the second phase, SVM is used for classification. Kulkarni et al. [11] presented a method using ANN together with Gabor filter for feature extraction to detect plant diseases at the early stage, which gives an accuracy rate of up to 91%. The model in this work used the combination of texture and color features for classification.

15.2.3 Feature selection

In feature selection (FS), we select a small number of features and ignore the irrelevant, noisy features for easier subsequent analysis, based on the redundancy and relevance. Based on these two characteristics, Yu et al. [12] in 2004 have classified the feature subset into four types: noisy and irrelevant, redundant and weakly relevant, weakly relevant and nonredundant, and strongly relevant. A feature that is not required for predicting accuracy is defined as an irrelevant feature. There are many approaches that can be implemented with filter and wrapper methods such as models, search strategies, feature quality measures, and feature evaluation. Set of features acts as key factors for determining the hypothesis of the predicting models. The number of features and the size of the hypothesis space are directly proportional to each other, that is, as the number of features increases, the search space size is also increased. One such case is that if there are M features with the binary class label in a dataset, then it has 2^{2^M} combination in the search space.

There are three types of FS methods, which are based on the interaction with the learning model such as filter, wrapper, and embedded methods. The filter method selects features based on statistical measures. It is independent of the learning algorithm and thus requires less computational time. Statistical measures such as information gain, chi-square test [13], Fisher's score, correlation coefficient, and variance threshold are used to understand the importance of the features. In contrast, the wrapper method's performance highly depends on the classifier. The best subset of features is selected by evaluating the results of the classifier. Wrapper methods take more time to run than filter methods, due to the fact that it needs to run together with the classifier many times. Some of the wrapper examples are recursive feature elimination [14], sequential FS algorithms [15], and genetic algorithm (GA). The third approach is the embedded method that utilizes ensemble learning and hybrid learning methods for FS. This method has a collective decision; therefore, its performance is better than the previous one. An example is random forest. It is more efficient than wrapper ones. A major drawback of embedded method is that it is specific to a learning model.

Many evolutionary meta-heuristics-based FS methods are also proposed; many of them are wrapper type since it has been proven that wrapper provides better performance [16]. Too et al. [17] proposed a competitive binary grey wolf optimizer (CBGWO), which is based on the grey wolf optimization (GWO) [18], to classify electromyography (EMG) signals. This work showed that CBGWO outranked other algorithms in terms of performance for that case study. Many other wrapper-based FS algorithms were also introduced in many previous works, including binary particle swarm optimization [19], GA [20], binary grey wolf optimization [21], ant colony optimization [22], and binary differential evolution [23].

15.3 Our proposed framework

15.3.1 Dataset

Our data contains 450 images of mango leaves, which belongs to four different types (three diseases and one healthy): anthracnose, gall midge, powdery mildew, and healthy. These are also four classes in our classification as in Figure 15.1. The samples are collected from various places in An Giang province, which is known as one of the places with the largest production of mango in Vietnam. The images are captured using a smartphone camera in the resolution of 3,096 × 3,096 pixels with no background as shown in Figure 15.2.

The proposed model for mango disease identification is shown in Figure 15.3, in which there are four main stages. To begin with, by rescaling, the images in the dataset are converted into lower resolution, compared with the original size. Then, center alignment step is responsible for guaranteeing the region of a leaf to be in center of image fitting exactly top and bottom of the image. Since there are various contrasts in leaf images, we apply the contrast enhancement method to adjust pixel intensities which benefit when providing more information in some areas of an image. The image dataset will be split into training and testing set. Finally, the CNN models are used to classify the given images.

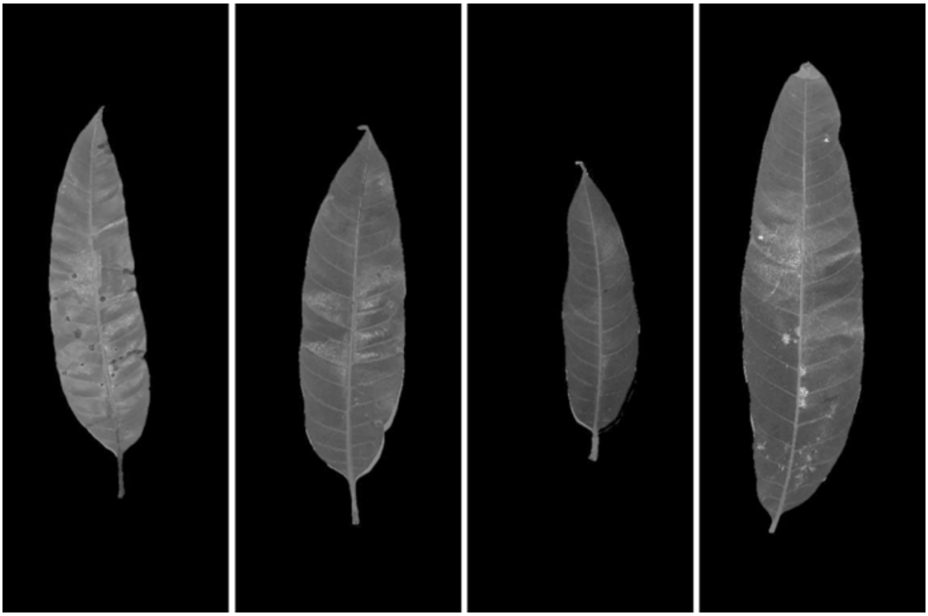

Figure 15.1: Four classes of leaf diseases in this chapter: anthracnose, gall midge, healthy, and powdery mildew.

15.3.2 Image preprocessing

Since the leaves have different sizes, it is necessary to perform rescaling to ensure that the training and testing images have the same dimension. Rescaling is performed to compress the original images to lower resolution ones, 256 × 256 pixels to be exact.

First, the image is segmented and binarized to find the minimum bounding box. The vertical size of the bounding box was used to rescale to 256 pixels to ensure the top and bottom leaves fit exactly to the top and bottom of the scaled images. The horizontal size of the bounding box will be used to shift the leaf image into the exact center of the scaled image.

Due to various contrasts in leaf region, many contrast enhancement methods are presented as in reference [13] to change pixel intensities which benefit in case of providing more information in some areas of an image. The image dataset will be also divided into training and testing parts, and then it is tested on CNN models.

Many contrast enhancement methods have been widely applied to improve the quality of the image [24]. In this chapter, to ameliorate features, which are low contrast to achieve improvement in terms of contrast quality, we use a contrast enhancement approach as in reference [25] before further analysis. The main idea of

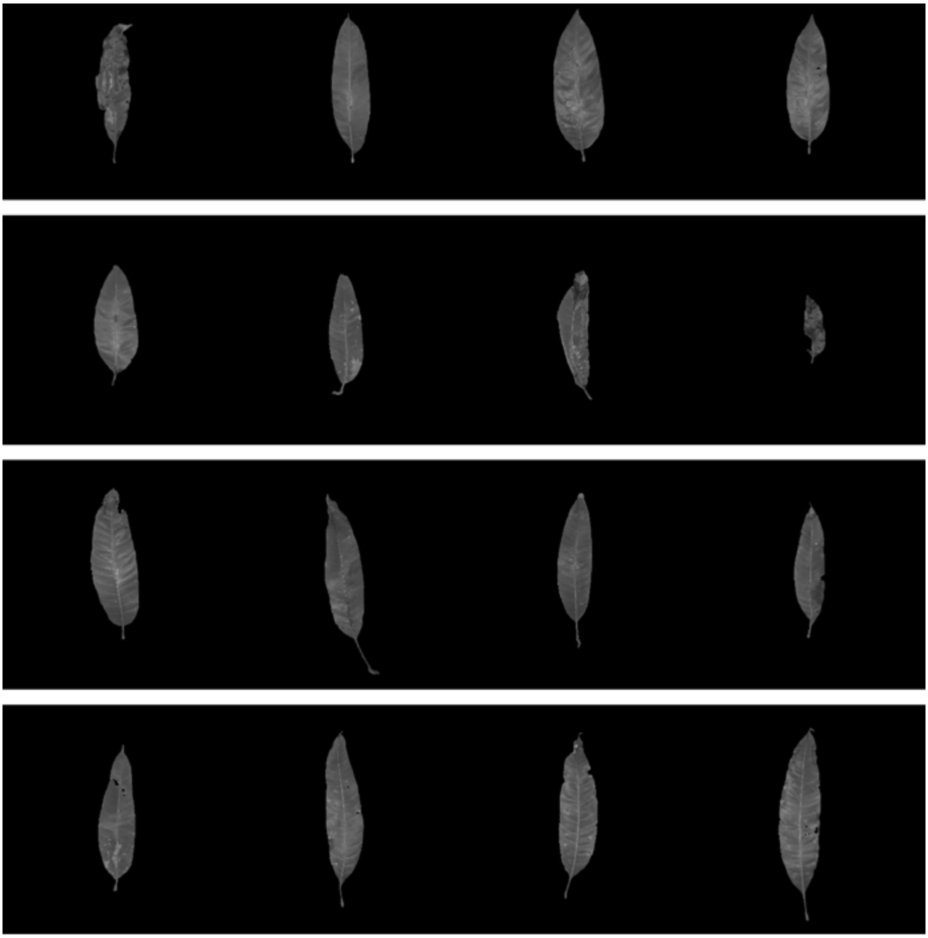

Figure 15.2: A small set of our dataset.

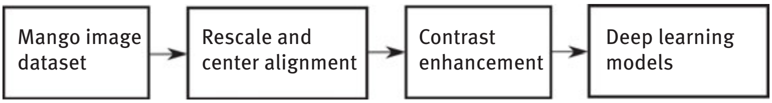

Figure 15.3: Approach using deep learning.

this method is to preserve the mean brightness of an input image during contrast adjustment in local regions. First, the input image in RGB color channels is converted into Hyperspectral Imaging (HSI) ones. This approach only focuses on the intensity parameter and preserves other hue and saturation values. Afterward, the intensity is divided by separator into two subparameters, which are high

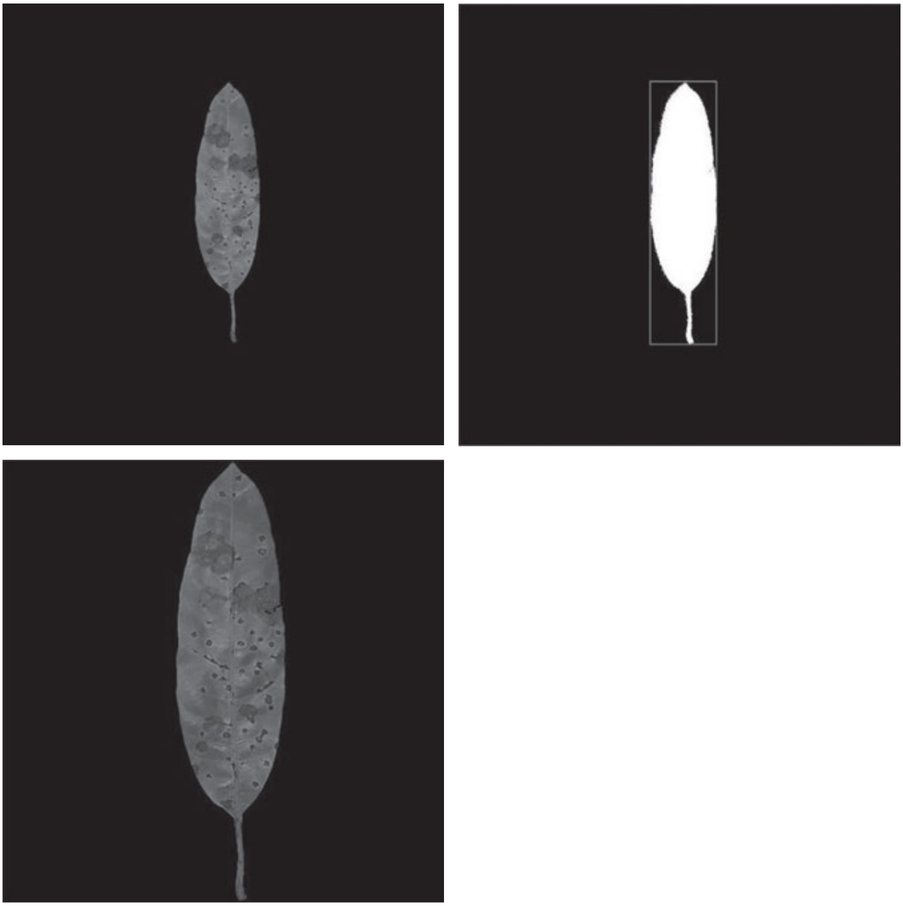

Figure 15.4: An example of rescaling and center alignment for a leaf image: original image; corresponding image with bounding box, and final rescaled and center-aligned images.

and low groups. This is done by the golden section search method shown in the following equation:

$$\gamma_{\text{hi}} = \{\gamma(i) | i > \gamma_m\}, \quad \gamma_{\text{lo}} = \{\gamma(j) | j \leq \gamma_m\} \tag{15.1}$$

where γ_{hi} and γ_{lo} are intensities of high and low groups, respectively, γ_m is a trial threshold intensity value, which is defined to divide the image into two subimages (Figures 15.4 and Figures 15.11). After obtaining estimates of the two sub-parameters of intensity, a combination of them is performed to achieve the enhanced intensity. The enhanced intensity is calculated by the following equation:

$$\gamma_{\text{enhance}}(i) = \gamma_{\text{lo}} + \left(\gamma_{\text{hi}} - \gamma_{\text{lo}}\right) \times \chi(i) \tag{15.2}$$

where $\chi(i)$ is the cumulative intensity of pixel i. To ensure minimum brightness error, the values of calculated mean brightness and input brightness are compared. In other words, iteration of this process is performed until an optimal value of enhanced intensity is obtained. Eventually, enhanced intensity and other initial hue and saturation values are combined and converted back to RGB color channel to give output image. The contrast enhancement effect is illustrated in Figure 15.5.

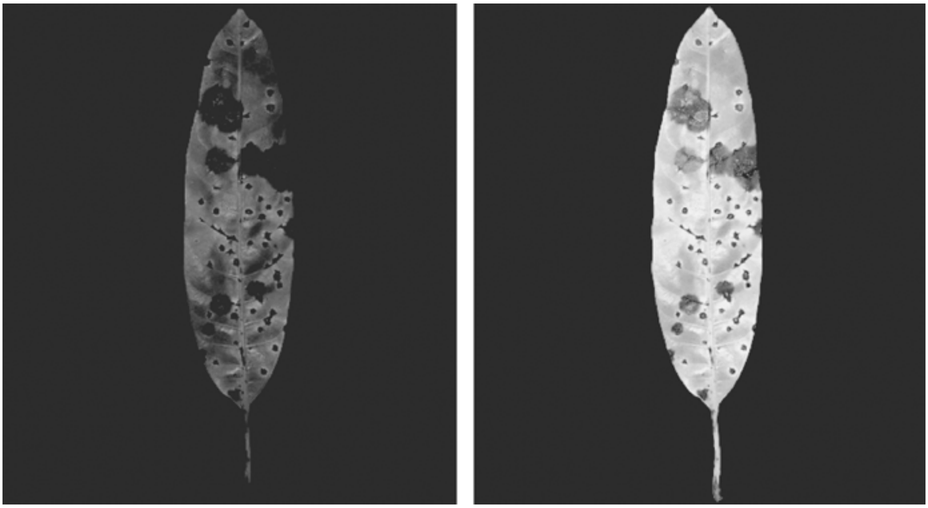

Figure 15.5: Contrast enhancement effect: before and after.

15.3.3 Convolutional neural network

ConvNet or CNN is a DL model that uses an input image, assigns weights, and biases to different aspects/objects. CNN requires less preprocessing than other algorithms. While in early models, filters are selected manually. After some learning, CNNs can approximate those filters.

In this chapter, we use popular CNN models, namely, AlexNet and VGG16.

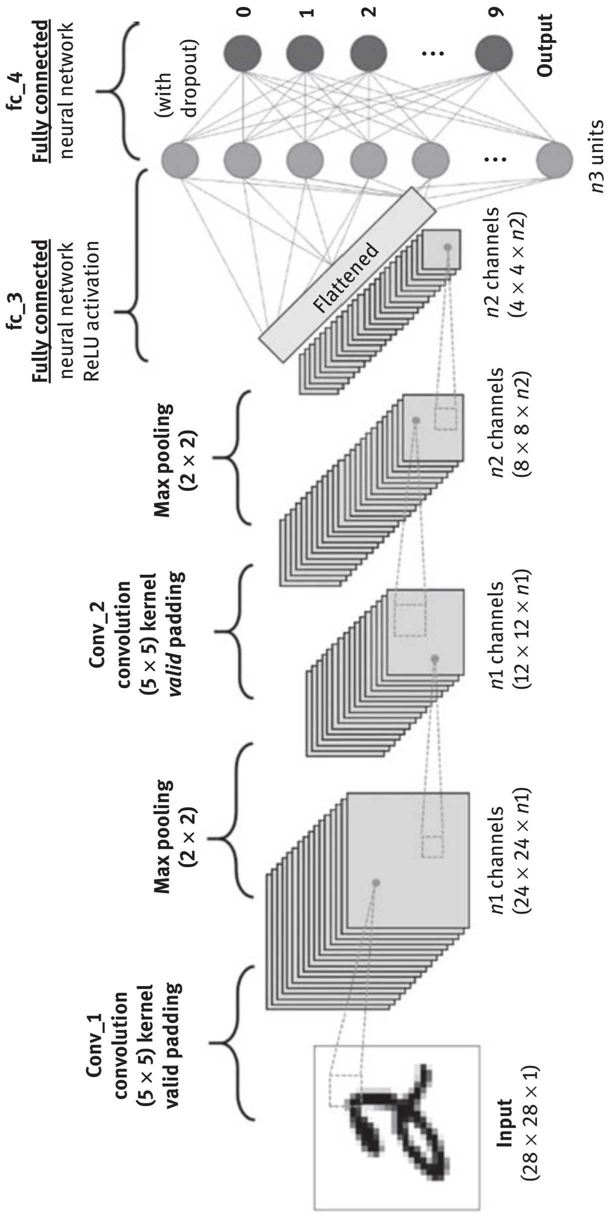

Figure 15.6: An example of a CNN for handwritten characters recognition (towardsdatascience.com).

15.3.3.1 AlexNet (2012)

AlexNet [26] was an architecture to tackle large labeled datasets for image recognition with higher precision and efficiency. AlexNet introduced various key design innovations like the addition of dropout layers for higher accuracy along with incorporation of distributed processing for better scalability and faster training. Hence, leveraging a multi-GPU system can speed up training as well as evaluation for large datasets. AlexNet sets the premise to better image classification architectures and research using DL techniques and methods.

AlexNet has five convolution neural layers (NLs) and three fully connected (FC) layers as in Figure 15.6. The architecture of AlexNet used ReLU activation function in its NLs to accommodate faster training over traditional activation functions like tanh. Feedback of normalization of the average data of a given layer during training Preventing static learning iterations and high false positives in recognition. The max pooling layers helped to reduce variance and also captured strong inputs over the network layers. Pooling layers are placed after the response normalization layers. The architecture uses overlapping pooling in its structure.

The convolutional layers are split to contain mapped kernels in the same graphical processing units (GPU). The convolutional layers reduce the image parameters producing 4,096 dimensional features for the FC layer that are mapped to a logistic regression output containing 1,000 classes. This architecture uses various kinds of transformations for data augmentation to increase learning. These spatial transforms provide more robust training samples for the network.

15.3.3.2 VGG16 (2014)

VGGNet [27] is a DL model. It improves AlexNet by using 33 filters in a steady progression. Figure 15.8 shows the VGG16 architecture.

For a given test image, the VGG network determines a likelihood – in the range of 0 and 1 – for every classes and selects the one with the highest likelihood. A downside of VGG16 is that there are many parameters to be trained, leading to a longer training time.

In the training process, TL is applied to fine-tune the models. Initially, the model was trained by the PlantVillage dataset, which was published in [5]. This dataset contains about 56,000 leaf images of 19 crops with 38 types of diseases. Thus, based on PlantVillage dataset, we can get a pretrained model that is used to apply TL to our problem. We divide the entire dataset into two parts: training and testing. The cross-entropy is used as a loss function (LF) to estimate the error prediction after classification layer. We use stochastic gradient descent algorithm with momentum to recalculate weights/biases at each iteration. We choose 30 epochs with an initial learning rate of 0.0005 and dropping every 10 epochs by 1/10. Table 15.1 & 15.4 presents more details.

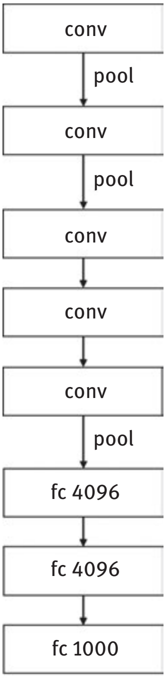

Figure 15.7: AlexNet architecture.

15.4 Results

We use 80% of the data for training and 20% for testing. Then the training set is again split into 80% for training and 20% for validation.

All the models are implemented on a desktop PC with GPU GTX 1070 that has 1920 CUDA cores with processor Intel(R) Core(TM) i7-7700 at 3.6 GHz, 32 GB of DDR4 RAM, and an SSD of 128 GB.

15.4.1 Conventional models

VGG16 achieved 74.63% of training accuracy and 83.52% of accuracy on the test set. AlexNet achieved 74.34% of training accuracy and 66% accuracy on the test set. As expected, with more convolutional layers, VGG model shows better ability to remove unwanted information. This helps with the prediction accuracy as shown in Figures 15.9 and 15.10. However, AlexNet provides slightly better confusion matrix results.

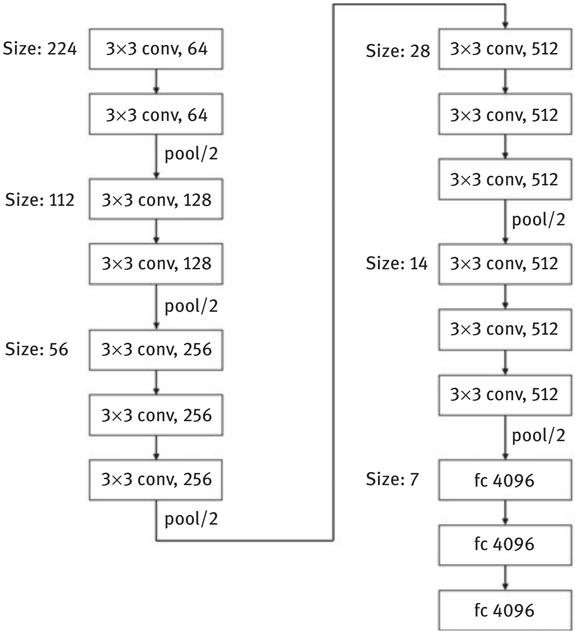

Figure 15.8: VGG16 architecture.

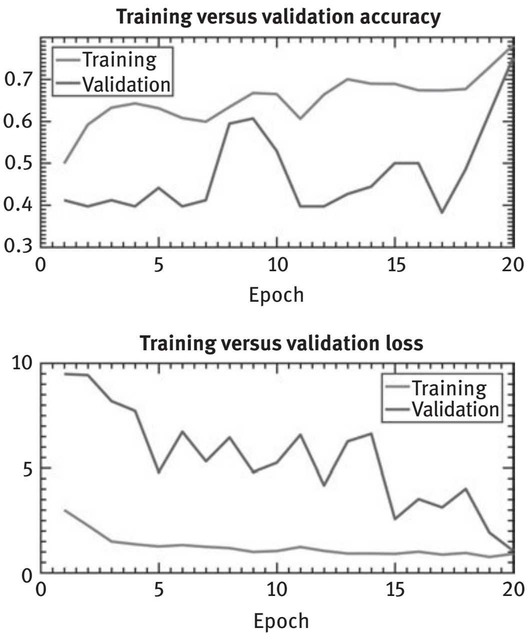

Figure 15.9: Training and validation result of VGG.

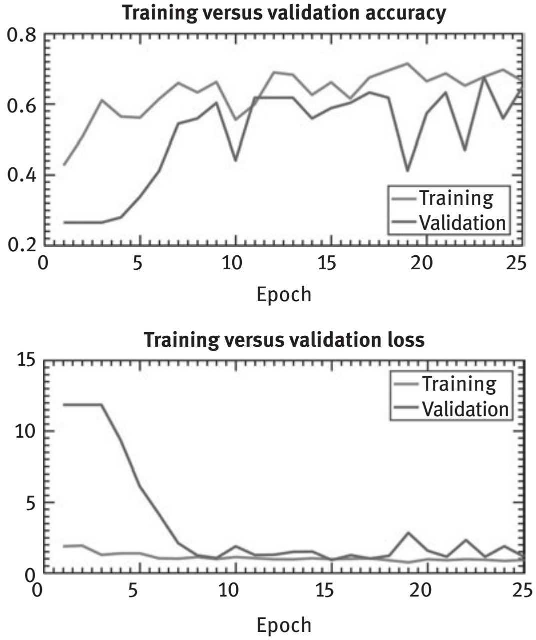

Figure 15.10: Training and validation result of AlexNet.

Table 15.1: Confusion matrix of VGG model.

Class	C1	C2	C3	C4
C1	34	3	0	0
C2	7	5	0	0
C3	3	0	24	0
C4	5	0	0	4

C1, anthracnose; C2, gall midge; C3, healthy; C4, powdery mildew.

Table 15.2: Confusion matrix of AlexNet model.

Class	C1	C2	C3	C4
C1	37	0	0	0
C2	7	4	0	1
C3	0	0	27	0
C4	5	1	0	3

C1, anthracnose; C2, gall midge; C3, healthy; C4, powdery mildew.

15.4.2 Models with transfer learning

We also perform TL to fine-tune this dataset. Initially, the model was trained by the PlantVillage dataset that consists of about 56,000 leaf images of 19 crops with 38 types of diseases. This gives an advantage that a huge amount of data is used to train this model, which can learn features efficiently. After having the pretrained model, we continue to train it on our dataset. In this part, AlexNet, ResNet 18, and ResNet 50 are considered.

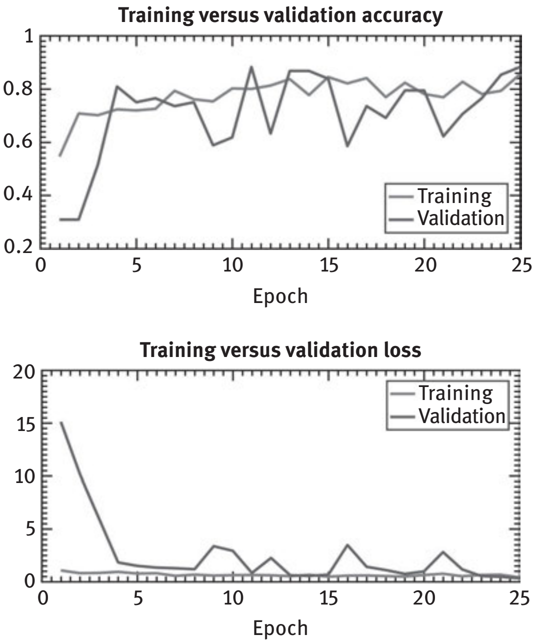

Figure 15.11: Training and validation result of AlexNet with transfer learning.

AlexNet with TL achieved 85.6% training accuracy and 78.8% testing accuracy; as expected, it is a marked improvement over the conventional model (74.3% training accuracy and 66% validation accuracy) (Figure 15.11–Figure 15.20).

With TL, VGG16 also obtains better results. The training accuracy and testing accuracy improve to 84.5% and 77.6% over the old results of 78% and 76%, respectively.

Table 15.3: Confusion matrix of AlexNet with transfer learning.

Class	C1	C2	C3	C4
C1	31	2	0	0
C2	5	15	0	0
C3	0	0	19	0
C4	5	4	2	2

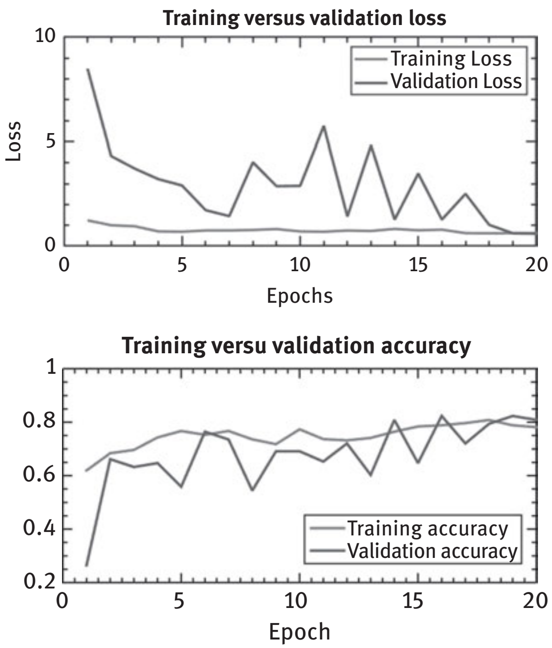

Figure 15.12: Training and validation result of VGG16 with transfer learning.

Table 15.4: Confusion matrix of VGG16 with transfer learning.

Class	C1	C2	C3	C4
C1	26	0	0	2
C2	4	8	0	4
C3	0	0	28	1
C4	6	2	0	4

15.4.3 Multilayer perceptron (MLP) approach

15.4.3.1 Feature extraction

Contrast-limited adaptive histogram equalization (CLAHE) was introduced by Zuiderveld in 1994 [28]. The method improves the original histogram equalization by using small tiles instead of the full image. Here, the original image is converted to HSV format, and CLAHE is applied to the H channel to enhance the contrast of the defective regions. The defective regions are then separated and mapped back to the original image. Table 15.6 presents more details.

The features considered in this chapter include the following:

Statistics-based: mean, standard deviation, skewness, and kurtosis of color channels (R, G, B, H, S, V).

15.4.3.1.1 Geometry based

- Defect area
- Defect perimeter: measured by the length of defected region boundary
- Major/minor axis length: lengths (in pixels) of the major/minor axis of an ellipse having the same normalized second central moments as the separated blob
- Eccentricity is calculated by dividing the distance between the foci and the major axis length
- Orientation: angle between the x-axis and the major axis of the above-mentioned ellipse, from −90° to 90°
- Convex area: area generated by the convex hull of the blob.
- Equivalent diameter of a circle having the same area as the blob is calculated as follows:

$$\sqrt{\frac{4 \times \text{Area}}{\pi}}$$

- Solidity: ratio of the blob area over the convex area is calculated as follows:

$$\frac{\text{Area}}{\text{Convex area}}$$

- Ratio of the pixels in the region to pixels in the total bounding box.

15.4.3.1.2 Texture based

- Mean of gray-level co-occurrence matrices.

There are 36 features in this case.

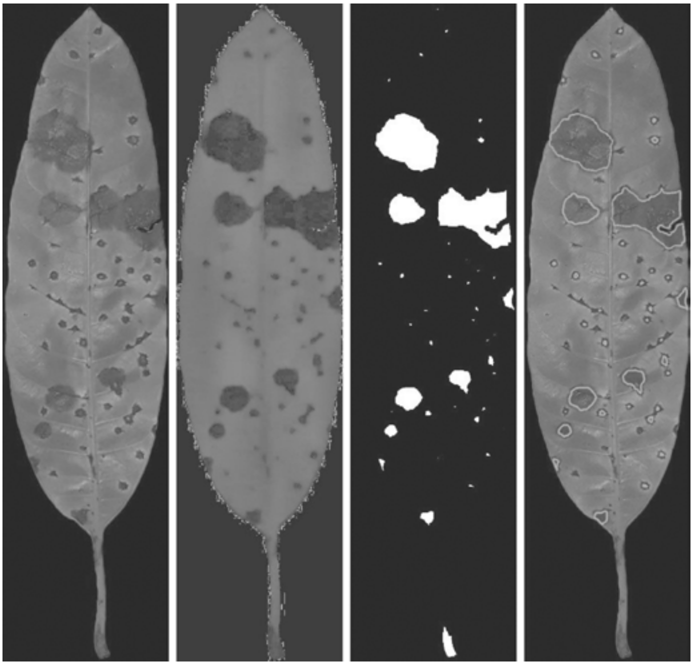

Figure 15.13: Feature extraction: original image, CLAHE is applied on H channel, extracted defective regions, and final result.

15.4.3.2 Feature selection

In this chapter, we implement a wrapper-based FS with a hybrid meta-heuristic called adaptive particle–grey wolf optimization (APGWO), which are combined from particle swarm optimization (PSO) and GWO.

15.4.3.2.1 Particle swarm optimization

PSO [29] imitates the swarm's flocking pattern. In PSO, each individual explores the search space with a velocity modified according to its own experience and its swarm's experience. Position of ith particle is $X_i = \left(x_i^1, x_i^2, \ldots, x_i^k\right)$. The best previous position that gives the best fitness value of that particle is saved and defined as p_i^{best}. The index of the best particle in the population is noted as g_{best}^k. The velocity of that particle is $V_i = \left(v_i^1, v_i^2, \ldots, v_i^k\right)$.

The model of PSO is represented as follows:

$$v_k^{t+1} = w * v_k^t + c_1 * \text{rand} * \left(p\text{best}_k^t - x_k^t\right) + c_2 * \text{rand} * \left(g\text{Best} - x_k^t\right) \quad (15.3)$$

$$x_k^{t+1} = x_k^t + v_k^t \quad (15.4)$$

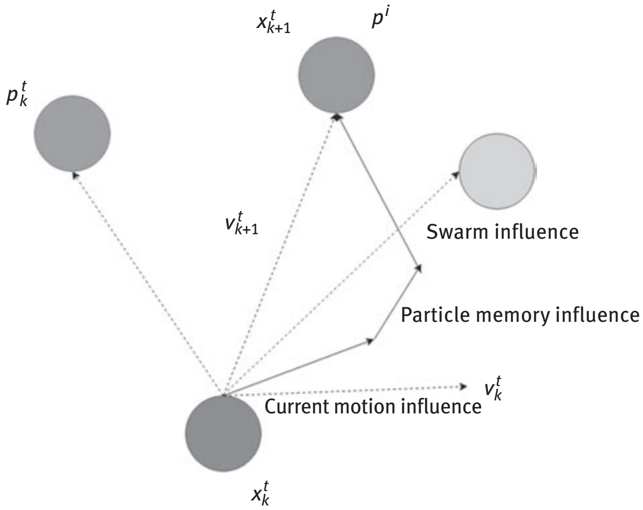

Figure 15.14: Position updating in PSO.

where c_1 and c_2 are two constants, and rand is any random number between [0, 1]. The term $c_1 * \text{rand} * \left(p\text{best}_k^t - x_k^t\right)$ is called "cognitive component" while $c_2 * \text{rand} * \left(g\text{Best} - x_k^t\right)$ is referred to as "social component."

15.4.3.2.2 Grey wolf optimization

GWO [18] is also a swarm algorithm based on hunting behavior of wolves. This algorithm also focuses on the social dominant hierarchy of the wolf. "Wolf alpha" is the leader representing the best solution.

"Wolf beta" and "Wolf omega" are the second rank and third rank leaders of the pack and stand for the second and the third best solution.

To develop the mathematical model, first, the fittest solution is considered as the alpha, and the beta and delta are considered as the second and the third fittest solutions, respectively. The next step is to update the positions using the following equations:

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_{\mathrm{p}}}(t) - \vec{X}(t)\right| \tag{15.5}$$

$$\vec{X}(t+1) = \overrightarrow{X_{\mathrm{p}}}(t) - \vec{A}.\vec{D} \tag{15.6}$$

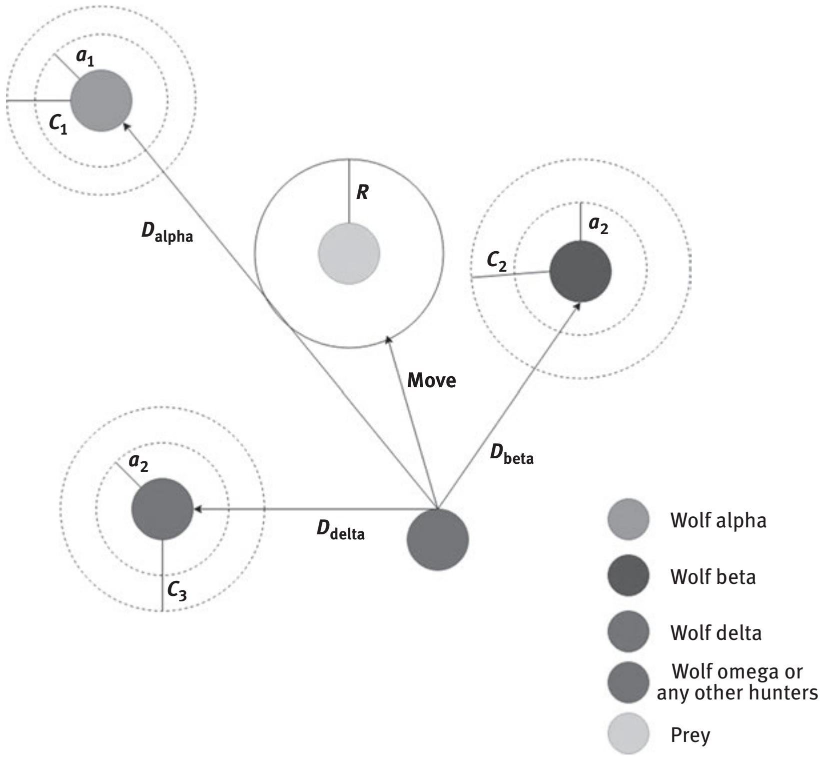

Figure 15.15: Position updating in GWO.

where t is the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\overrightarrow{X_p}$ is the position of the target, and $\vec{X}$ is the position of a wolf. The coefficient vectors are calculated by equations:

$$\vec{A} = 2\vec{a}\ .\vec{r}_1 - \ \vec{a} \tag{15.7}$$

$$\vec{C} = 2\vec{r}_2 \tag{15.8}$$

where $\vec{a}$ is linearly decreased from 2 to 0, and $\vec{r}_1$ and $\vec{r}_2$ are random vectors in [0, 1].

The following step is hunting, which defines the final position of the wolf $\vec{X}(t+1)$ using these equations:

$$\vec{D}_\alpha = \left|\vec{C}_1 . \overrightarrow{X_\alpha} - \vec{X}\right| \tag{15.9}$$

$$\vec{D}_\beta = \left|\vec{C}_2 . \overrightarrow{X_\beta} - \vec{X}\right| \tag{15.10}$$

$$\vec{D}_\delta = \left| \vec{C}_3 . \overrightarrow{X_\delta} - \vec{X} \right| \tag{15.11}$$

$$\vec{X}_1 = \overrightarrow{X_\alpha} - \overrightarrow{A_1} . \overrightarrow{D_\alpha} \tag{15.12}$$

$$\vec{X}_2 = \overrightarrow{X_\beta} - \overrightarrow{A_2} . \overrightarrow{D_\beta} \tag{15.13}$$

$$\vec{X}_3 = \overrightarrow{X_\delta} - \overrightarrow{A_3} . \overrightarrow{D_\delta} \tag{15.14}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{15.15}$$

15.4.3.2.3 Proposed APGWO heuristic

The values of c_1 and c_2, which are usually called "acceleration coefficients," are often set as constants, most likely $c_1 = c_2 = 1$ or $c_1 = c_2 = 2$. These values are found by empirical studies in order to balance the cognitive and social components, which also balance the exploration and exploration phases. In this chapter, we propose a formula to change the acceleration coefficients in each iteration. The new coefficients are calculated as follows:

$$c_1^t = 1.2 - \frac{f\left(x_k^t\right)}{f(g\text{Best})} \tag{15.16}$$

$$c_2^t = 0.5 + \frac{f\left(x_k^t\right)}{f(g\text{Best})} \tag{15.17}$$

where c_1^t and c_2^t stand for the coefficients at iteration t, $f\left(x_k^t\right)$ is the fitness of particle k at iteration t, and $f(g\text{Best})$ is the swarm's global best fitness. The values of 1.2 and 0.5 are also found by empirical studies. We also modify the formula for inertia as follows:

$$w_t = (\text{maxIter} - t) * \frac{w\text{Max} - w\text{Min}}{\text{maxIter}} + w\text{Min} \tag{15.18}$$

Finally, we update the velocity and position of particles by the following equations:

$$v_k^{t+1} = w * v_k^t + c_1^t * \text{rand} * \left(p\text{best}_k^t - x_k^t\right) + c_2^t * \text{rand} * \left(g\text{Best} - x_k^t\right) \tag{15.19}$$

$$x_k^{t+1} = x_k^t + v_k^t \tag{15.20}$$

Şenel et al. [30] provided a novel hybrid PSO–GWO by replacing a particle of the PSO with a value being the mean of the three best wolves' positions. In this chapter, we introduce a probability of mutation, which will trigger a small number of iterations of GWO within the PSO main loop. The pseudocode for this algorithm is given as follows:

```
Initialize the particle population
Initialize parameters
while (t< Max number of iteration)
for each particle with position x_p
calculate fitness value f(x_p)
if f(x_p) is better than pbest_p then
 pbest_p ← x_p
endif
if f(pbest_p) is better than gbest then
 gbest ← pbest_p
endif
end for
update w according to equation (16)
for each particle with position x_p
update c1, c2 according to equation (14), (15)
calculate velocity of each particle by equation (17)
update position of each particle by equation (18)
end for
if rand (0,1) < prob
run GWO
x_p = position of the best wolf
endif
t=t+1
end while
return gbest
```

Figure 15.16: Pseudocode for APGWO.

The proposed algorithm is tested on 23 multimodal functions given in [18], which have many local optima. The problem becomes worse with higher dimensional cases and usually used to benchmark meta-heuristic algorithms. The proposed APGWO yields competitive results compared with the standard PSO and GWO algorithms.

APGWO was first implemented in solving capacitated vehicle routing problem with clustering approach [31], which also yields competitive results compared with GWO and PSO.

15.4.3.2.4 Wrapper-based APGWO

The solution for the wrapper is a binary array, with dimension of $1 \times n$, where n is the total number of features. Selected features will take value of 1, and 0 otherwise.

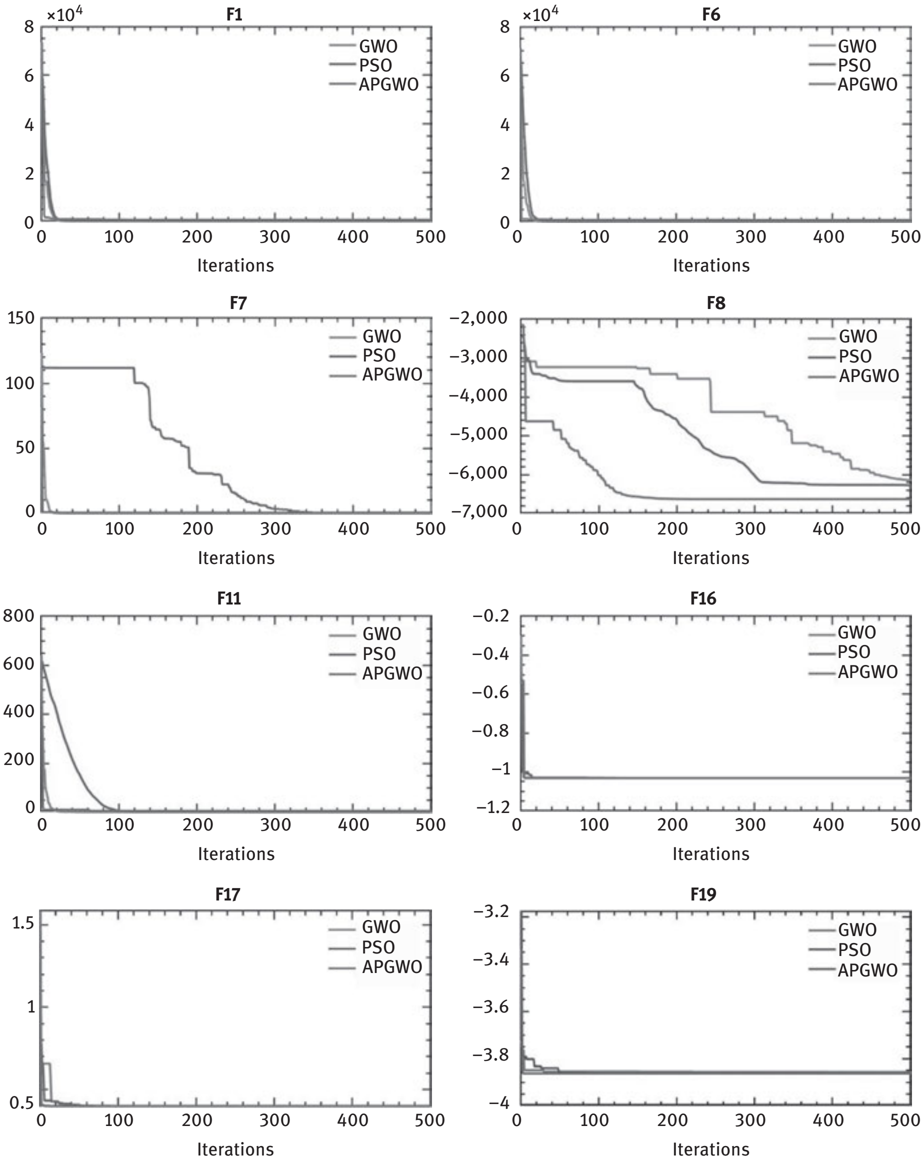

Figure 15.17: Benchmarking results of the proposed APGWO.

The parameters set for different algorithms are as follows: 20 search agents (for PSO main loop), 20 search agents (for nested GWO loop), 20 iterations for main PSO loop, 5 iterations for nested GWO, and wMax = 0.9 and wMin = 0.2.

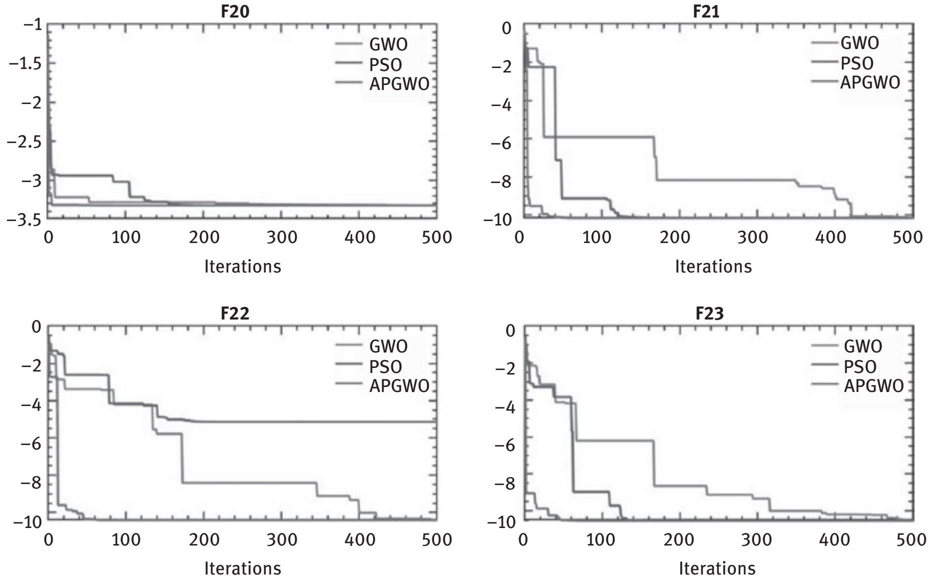

Figure 15.17 (continued)

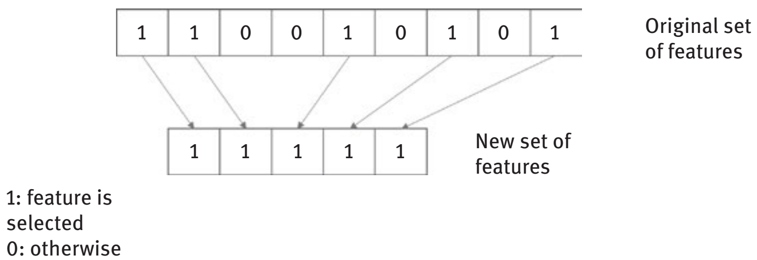

Figure 15.18: Binary feature selection process.

The fitness function is defined as follows:

$$\text{Maximize}\, E$$

where E is the accuracy of the model with regard to the test set.

The model considered is an MLP with the following architecture:

- Input layer: number of features.
- Hidden layers 1, 2, and 3 having 30, 20, and 10 neurons, respectively, with ReLU activation function.
- Output layer: four neurons with softmax activation function, corresponding to four classes.

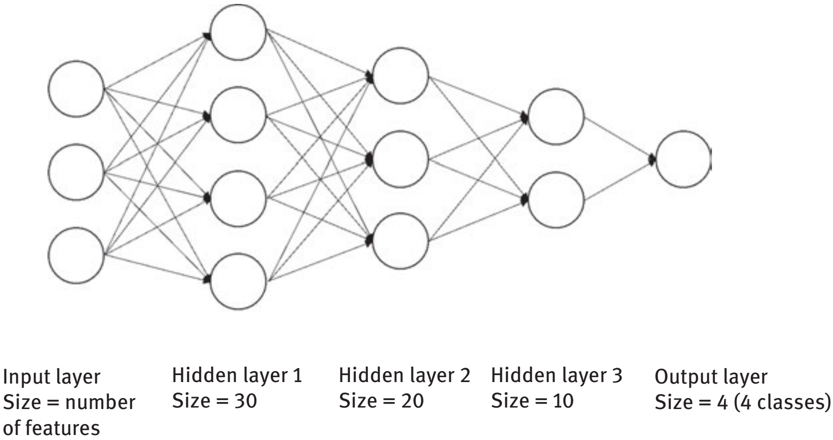

Figure 15.19: Proposed MLP architecture.

ReLU function is used in the hidden layers due to its special characteristics. It does not activate all the neurons at the same time, only when the input is positive. Due to this, ReLU is more computationally efficient in comparison with sigmoid or tanh function. The softmax function is chosen for the output layer due to the multi-class classification problem. The LF is also categorical cross-entropy.

The model is run within the algorithm as the cost function. After reaching the maximum iteration, the best subset of feature is obtained.

After running for 20 iterations, the best solution is [1 1 0 1 1 1 0 1 0 1 0 1 1 1 0 1 1 1 1 1 1 1 1 1 1 0 1 0 1 0 1 0 0 0 0 1], which means there are 24 features which are selected out of 36. Details of the solution are in Table 15.5.

After that, this subset of features is used to train the MLP with 50 epochs, which yields the following result:

In this approach, MLP achieved 85.2% of training accuracy and 81.2% of testing accuracy, and with this approach, the training time is significantly lower than the CNN models.

It can be seen that between the two CNN models, VGG16 is better than AlexNet without Tensorflow Lite (TF), and TF only slightly enhances its performance. In contrast, AlexNet's performance is increased significantly after TF, and it outperforms VGG16 despite having a less amount of parameters. Table 15.8 presents the detailed comparison.

Table 15.5: Details of selected features.

	Before FS	After FS
Statistical features	Mean *R*, mean *G*, mean *B*, mean *H*, mean *S*, mean *V*, *R* standard deviation, *G* standard deviation, *B* standard deviation, *H* standard deviation, *S* standard deviation, *V* standard deviation, *R* skewness, *G* skewness, *B* skewness, *H* skewness, *S* skewness, *V* skewness, *R* kurtosis, *G* kurtosis, *B* kurtosis, *H* kurtosis, *S* kurtosis, *V* kurtosis	Mean *R*, mean *G*, mean *H*, mean *S*, mean *V*, *R* standard deviation, *G* standard deviation, *B* standard deviation, *H* standard deviation, *S* standard deviation, *V* standard deviation, *R* skewness, *B* skewness, *S* skewness, *R* kurtosis
Geometric features	Defect area Defect perimeter Major axis length Minor axis length Eccentricity Orientation Convex area Equivalent diameter Solidity Ratio	Defect area Major axis length Eccentricity Orientation Convex area Equivalent diameter Extent Perimeter
Textural features	GLCM mean	GLCM mean

15.5 Conclusion

We have proposed an image-based method with preprocessing steps to identify diseases in mango leaf by using DL. Rescaling, center alignment, and contrast enhancement steps are used as preprocessing stages, which provide suitable adjustments to images before processing by the deep neural network. TL from other similar feature dataset is also performed in order to train the deep residual neural network, which gives advantages in the learning process. Of the two examined CNN models, AlexNet outperforms VGG16 after applying TF. We also introduced another MLP approach achieving an accuracy of 81.2%, which is higher than the accuracies of the two pretrained models. In future work, this presented method will be improved by increasing the number of images in dataset, optimizing parameters of the deep neural network models, as well as the ones of the APGWO wrapper.

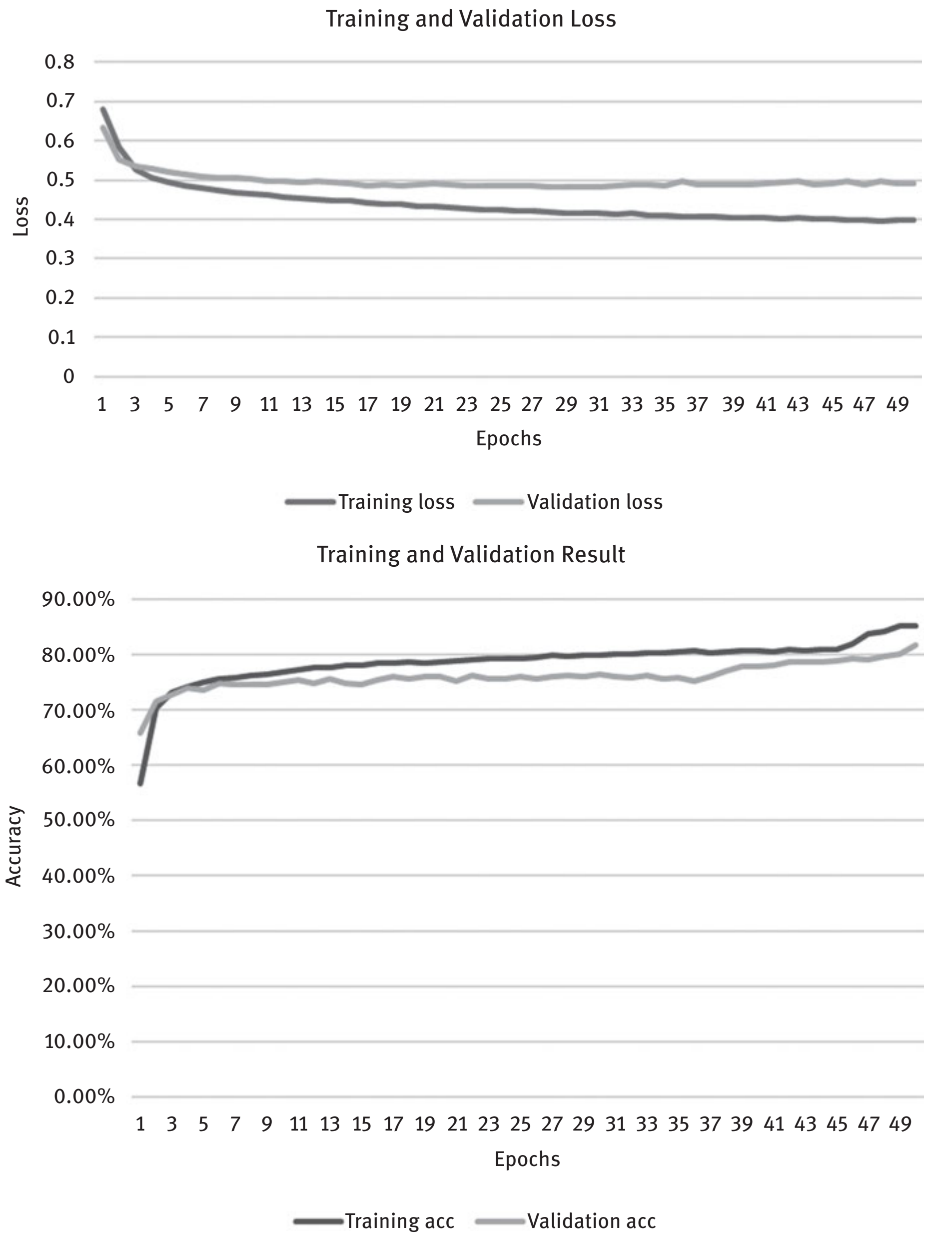

Figure 15.20: Result of MLP.

Table 15.6: Confusion matrix of MLP.

Class	C1	C2	C3	C4
C1	34	0	0	1
C2	7	13	0	0
C3	2	0	18	2
C4	3	0	1	4

Table 15.7: Performance comparison of CNN models.

Models	Without transfer learning		With transfer learning	
	Training accuracy	Validation accuracy	Training accuracy	Validation accuracy
AlexNet	74.3%	66%	85.6%	78.8%
VGG16	78%	76%	84.5%	77.6%

Table 15.8: Performance comparison of all models.

Models					
	Class	1	2	3	4
AlexNet without transfer learning	Recall	1.00	0.33	1.00	0.33
	Precision	0.76	0.80	1.00	0.75
	F1 score	0.86	0.47	1.00	0.46
VGG16 without transfer learning	Recall	0.92	0.42	0.89	0.44
	Precision	0.69	0.63	1.00	1.00
	F1 score	0.79	0.50	0.94	0.62
AlexNet with transfer learning	Recall	0.94	0.75	1.00	0.15
	Precision	0.76	0.71	0.90	1.00
	F1 score	0.84	0.73	0.95	0.27
VGG 16 with transfer learning	Recall	0.93	0.50	0.97	0.33
	Precision	0.72	0.80	1.00	0.36
	F1 score	0.81	0.62	0.98	0.35
MLP	Recall	0.97	0.65	0.82	0.50
	Precision	0.74	1.00	0.95	0.57
	F1 score	0.84	0.79	0.88	0.53

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16 Using deep learning for image-based plant disease detection

Abstract: Recorded history indicates that diseases have been affecting plants for almost 250 million years. In underdeveloped countries, the access to disease control methods is limited which results in huge annual losses of majority of crops and consequently giving rise to lack of food and starvation. Early detection of the disease can ensure better crop management. The conventional methods for plant disease detection require a significant amount of expertise and thus incurring high costs. A combination of recent technologies like Internet of things (IoT) and deep learning (DL) can yield a cost-effective and an easy to implement solution. This chapter aims at exhibiting artificial intelligence (AI) (DL) capabilities to detect plant disease using images. An illustration with the largest publicly available dataset (PlantVillage) of plant disease leaf images has been implemented with DL architectures, to develop a disease classification model. Moreover, the ease and viability of deploying small-size DL models on AI–IoT edge devices are also discussed. Finally, the limitation of present data as well as the possible solutions is highlighted for the reader.

Keywords: agriculture, deep learning, image classification, machine learning, plant disease detection, Internet of things, artificial intelligence

16.1 Introduction

Plants are the roots of survival for every form of life on the Earth. For food, oxygen, or raw supplies, humans depend, if not, more than other species. The health of plants is essential to ensure not only ecological balance but also global economic sustainability and growth. Be it multibillion-dollar industries like dairy, textile, paper, and packaging, or the most fundamental food provision, each one is driven by quality and quantity of agricultural supplies in their value chain.

As per the estimate from the Food and Agriculture Organization of the United Nations (FAO), plant pests and diseases annually cause loss of $220 billion trade with up to 40% of food crops lost [1], resulting in substantial economic deficit and increasing food scarcity problem globally. Every year farmers worldwide face the

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https://doi.org/10.1515/9783110691276-016

problem of significant agriculture yield loss due to crop pathogens and pests (P&Ps). In the 2019 NEE report, five major crops making, 50% of the global human calories intake, have suffered significant deficits due to the P&Ps (11.0–32.4% in soybean, 10.1–28.1% in wheat, 19.5–41.1% in maize, 8.1–21.0% in potato, and 24. 6–40.9% in rice) [2].

To substantiate the criticality, year 2020 has been declared as the International Year of Plant Health by UN General Assembly. The agricultural production must increase to about 60% by 2050, according to the UN's estimates to fulfill the demand from increasing global population [3].

If the diseases caused by P&P's can be diagnosed timely and accurately, the losses can be minimized and completely avoided in best-case scenarios. Effective and efficient plant disease diagnosis would be a necessary step for state-of-the-art plant health management and ultimately for continued financial and natural growth of the world.

Hence, in this chapter, the authors observe the conventional disease detection methods and identify the problems or gaps. Furthermore, the potential of novel solution approach with advance tools and technologies like smartphones, Internet of things (IoT), and artificial intelligence (AI) (specifically deep learning (DL)) is clearly established with real-world use case. Typical DL system/model process and concepts are outlined. Moreover, practical implementation is elaborated with the help of an example.

16.2 Current scenario

At present, there are (1) direct methods and (2) indirect methods, used for identification of disease in crops due to pathogens like bacteria, viruses, and fungi. Well-known direct laboratory-based methods are polymerase chain reaction (PCR), immunofluorescence (IF), fluorescence in situ hybridization (FISH), enzyme-linked immunosorbent assay, flow cytometry, and gas chromatography–mass spectrometry; whereas indirect methods include thermography, fluorescence imaging, and hyperspectral techniques.

16.2.1 Direct detection methods

In direct detection methods, the pathogens, which are responsible for the disease, are detected directly to provide accurate identification of the diseases. To analyze large numbers of samples, molecular and serological methods can be used for high-throughput analysis.

16.2.2 Indirect detection methods

These methods are based on plant stress and variable profiling. They can be used for identifying biotic and abiotic stresses as well as pathogenic diseases in crops.

16.3 Concerns and challenges

16.3.1 Laboratory-based methods required high skilled analytics

Although direct plant disease detection techniques like PCR, FISH, and IF are quite capable of detecting plant pathogens with high sensitivity, their applications are limited to laboratory setup and specialized analytics. Imaging-based indirect methods like thermography and fluorescence imaging are susceptible to environmental changes and lack specificity of type of disease. Certainly, various biosensors can be applied to test in-field, but their application is limited to bacterial pathogens detection and cannot be used for fungal and viral pathogens. Also, the success is highly dependent on DNA probe produce for the test.

16.3.2 Complex sample preparation and time consuming

Sample preparation for laboratory-based plant disease detection methods require special skill, thus making it more complex. Also, it takes long time to complete process, from sample collection until data analysis.

16.3.3 No real-time detection

Most of the direct plant disease detection methods cannot provide real-time detection. Thus, it is not effective for early warning and prevention.

16.3.4 High cost involved

Most of the direct or indirect plant disease detection methods require certain special set-up or skills attracting significant fixed as well as on-going costs.

16.4 Application of image-based DL in plant diseases detection

In recent years, a subfield of machine learning (ML) called DL (DL) is being employed by various industries to automate mundane tasks and to solve complex problems. DL algorithms are based on artificial neural networks (ANNs). The idea of ANNs originates from distribution and processing of information in human brain structure. Many of the contemporary DL algorithms/models are built based on convolutional neural network (CNN), which is now a very popular choice for vision task such as image/object classification, detection, and segmentation. Experts perform visual inspection of plant tissue and evaluate the plant disease extremity. This results in high cost and stunted efficiency of disease assessment and hampers the growth of present-day agriculture [4]. Such situation calls for utilization of advanced methods like DL to get the state-of-the-art accuracy and higher process efficiency.

The widespread availability of smartphones makes them a primary resource of day-to-day image capturing. In addition to that, the high-resolution displays and computational power of these phones enable the integration of computationally intensive DL models easier with them. Collecting plant image data as well as diagnosis of disease in the plants have become uncomplicated because of smartphones.

Among other promising solutions is the implementation of quantized DL model on a low-cost computer module like Raspberry Pi with tiny memory and computation power. Such concepts can also be utilized to produce best results offline with minimum investment for on-field plant disease detection.

Implementation of disease detection based on plant images using deep convolutional neural network will be discussed in the current chapter. Some of the modified DL models developed over the last few years for disease diagnosis of plants will also be discussed here.

Moreover, to demonstrate the ease of implementation of DL models in plant disease detection, real-time example shall be discussed, using publicly available datasets along with fitting evaluation metrics.

16.4.1 Introduction to deep learning

DL is one of the most advanced areas within the ML field. DL is designed to emulate the human brain in order to process data, gain knowledge, and learn patterns and improve decision-making by machine. In other words, it represents an AI that can perform supervised, semisupervised, and unsupervised learning from data that are structured/unstructured and labeled/unlabeled. Popular DL architectures are deep neural networks (DNNs), CNNs, and recurrent neural networks. Fields like computer vision, audio processing, recommendation systems, translation, natural language processing (NLP), speech recognition, medical research, text generation, and automation in general employ these architectures. DL has been successful in automating tasks or predicting results comparable to human field experts and even surpassing in some tasks. In simplest words, DL is an ML technique to automate prediction. Unlike usual ML algorithms, DL algorithms are nonlinear that execute ML process with hierarchical level of ANNs. The adjective “deep” in DL refers to the use of multiple layers in the network – more the layers, deeper the network. Unlike usual neural networks, deep networks can have hundreds of layers Figure 16.1.

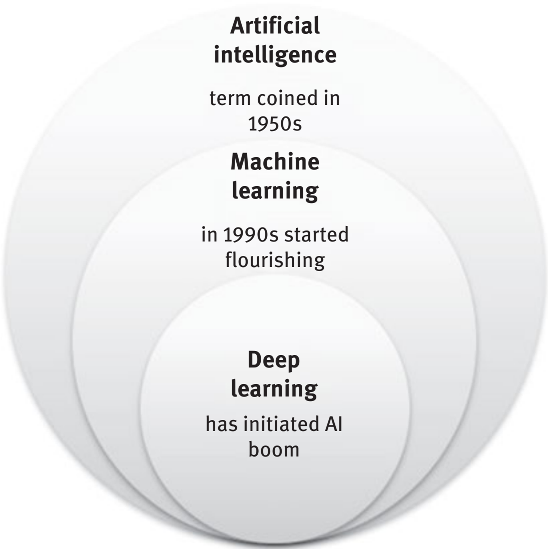


Figure 16.1: Difference between AI, ML, and DL.

John McCarthy, in 1956, came up with the term AI, though AI has stayed as more of a theoretical concept for many years. DL has recently become a flag bearer of AI. DL is actually a subset of ML which is further a subgroup of AI. The term DL was minted by Rina Dechter in 1986. In 2000, Igor Aizenberg and colleagues introduced DL to ANNs [5–7]. Many studies and researches about neural networks and DL algorithms were carried out through 1990s and 2000s. Although during this time, simpler supervised learning models such as support vector machines (SVMs) were preferred over ANNs due to lack of understanding brain networks and high computational cost. Yann LeCun in CERN colloquium [8] talked about the impact of DL in industry. According to him, in 2000s, CNNs were being used to process approximately 10–20% of all the checks written in the USA. The primary reasons for DL receiving more attention only in last decade are data and computational power.

In 2009, advances in hardware such as NVIDIA graphics processing units (GPUs) enabled renewed interest in DL. Around the same time, to build competent deep networks, Google Brain started experimenting with NVIDIA GPUs. Moreover, Andrew Ng drew a conclusion that GPUs are 100 times faster to execute DL system. GPUs reduce DL model training times to a few days from several weeks [9, 10]. Availability of large datasets such as ImageNet has contributed significantly to the progress of DL. A paper by Ciresan et al. at computer vision and pattern recognition (June 2012) recognized CNNs to be very significant in the future of computer vision field. The paper discussed improvement in multiple vision benchmarks by employing max-pooling CNNs with GPU. The large-scale ImageNet competition (October 2012) was won by Krizhevsky et al. [11] with a similar setup by a remarkable edge over simplistic ML methods. Furthermore, Ciresan et al.'s team dominated two medical image competitions, namely, the ICPR contest in November 2012 and the MICCAI Grand Challenge in 2013, on the topic of detecting cancer from images [12].

Other successful implementations in NLP and speech recognition have also contributed to DL revolution. Moreover, in the last couple of years, the concept of transfer learning has accelerated DL capabilities as well as has made the implementation easier.

16.4.2 How deep learning works

ANN is a collection of connected units, called artificial neurons, which are arranged in layers. The inputs pass through different layers and certain form of transformation is applied on them by every one of the layers. DNN is an ANN with inputs traversing through several layers between the input layer and the output layer.

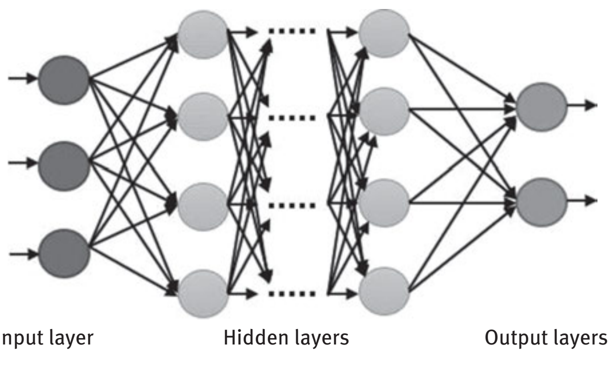


Figure 16.2: Deep neural network (DNN) architecture.

Figure 16.2 the DNN is competent to find the relation between input and output, irrespective of it being linear or nonlinear. DL uses numerous layers to incrementally draw out features from the data. At every layer, the network applies transformations and learns the pattern to produce an output model. Let us discuss an example. A DNN model is developed to recognize if the animal in an image is a cat or dog. Given image passes through the DNN and the probability that the animal being dog or cat is computed. So, here, the edges could be recognized by lower layers, while human friendly concept like face could be located by higher layers. A typical DNN would consist of input layer, several hidden layers, and output layer. Usually a neural network contains two to three hidden layers only; on the contrary, DNNs can have more than hundred hidden layers.

The DNN initializes with allocating random values to connections between the layers. These values are called weights. The inputs from data are multiplied with weights and return output in the range of [0, 1]. Usually the network does not predict accurately, or desired pattern is not learnt in the first few iterations. So, the algorithm would fine-tune the weights and reiterate. The algorithm keeps on tuning some of the parameters till it reaches the intended output with an acceptable level of accuracy.

If a typical ML method is to be implemented to predict what an image contains e.g. dog or cat, the relevant features need to be manually extracted from images. This process of feature extraction is quite arduous. In DL model the extraction of relevant features from images is automated process. Additionally, DL model is capable of learning jobs such as image classification automatically from input image data, executing end-to-end learning. In general, with an increase in the amount of data results in improved accuracy of DL model.

16.4.3 Convolutional neural network

CNN is one of the most popular classes of DNNs. They are being employed in majority of the DL applications such as image or video classification and detection, recommendation systems, and NLP. As the name suggests, CNNs involve an operation (mathematical) defined as convolution. Convolution is a linear operation whose task is to reduce dimension. In simplest words, CNNs are networks which, instead of simple matrix multiplication, use convolution operation [13].

As shown in Figure 16.3, CNN (also called ConvNet) consists of multiple layers, such as convolutional layers, rectified linear unit (ReLU) function for activation, max-pooling layers or average-pooling layers, and fully connected (FC) layers. These hidden layers convolve by multiplication or dot products. In general, ConvNet convolution is a linear multiplication operation of weights, called a filter or a kernel, with the input array.

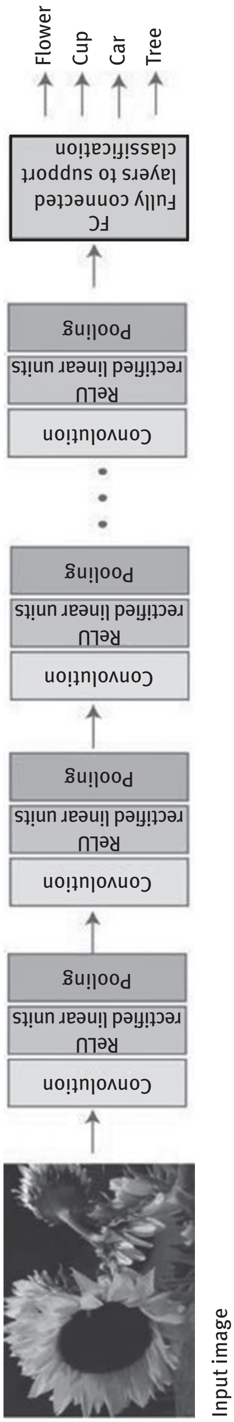


Figure 16.3: CNN layers (sourced from Mathworks online education series).

16.4.3.1 Convolutional layer and filter

An element-wise operation, a dot product, is utilized to multiply the input data and the filter. A dot product is performed between the filter and the patch of the input having the size of a filter. The filter is supposed to be smaller than the size of input, so that the same weights can be multiplied by the input multiple times at various patches on the input.

The filter moves on the image in a sliding window manner. The dot product is summed at the end, and hence it is also called scaler product. The output from the input array and the filter multiplication is a scalar value. The two-dimensional output array from this operation is called a feature map. Feature map value goes through nonlinearity, called ReLU.

In Figures 16.4 and 16.5, the lambda values (λ_1, λ_2, λ_3, λ_4) represent filter weights which are multiplied with an image resulting in single values (P, Q, R, S). The image is reduced to 2 × 2 size after application of a filter. To preserve, we can apply a 3 × 3 filter with zero padding on an image. This allows us to center the filter on each pixel, so that each original pixel corresponds to a pixel in the result.

An example of a filter applied to an image by using zero padding is shown in Figure 16.6 (a). The final result is shown in Figure 16.6(b).

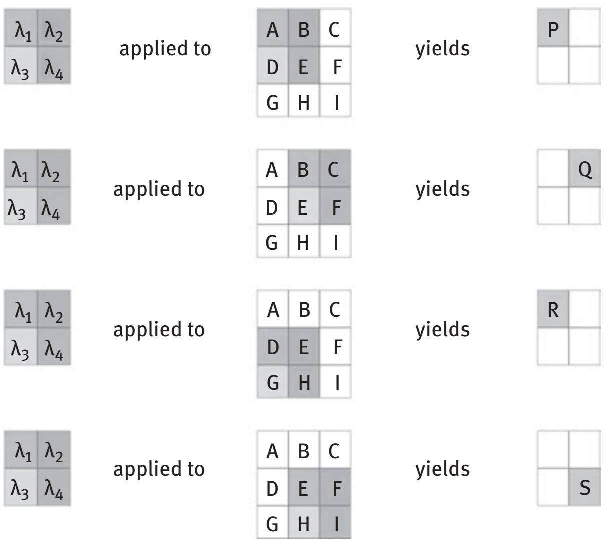


Figure 16.4: A filter of size 2 × 2 applied on a 3 × 3 size image.

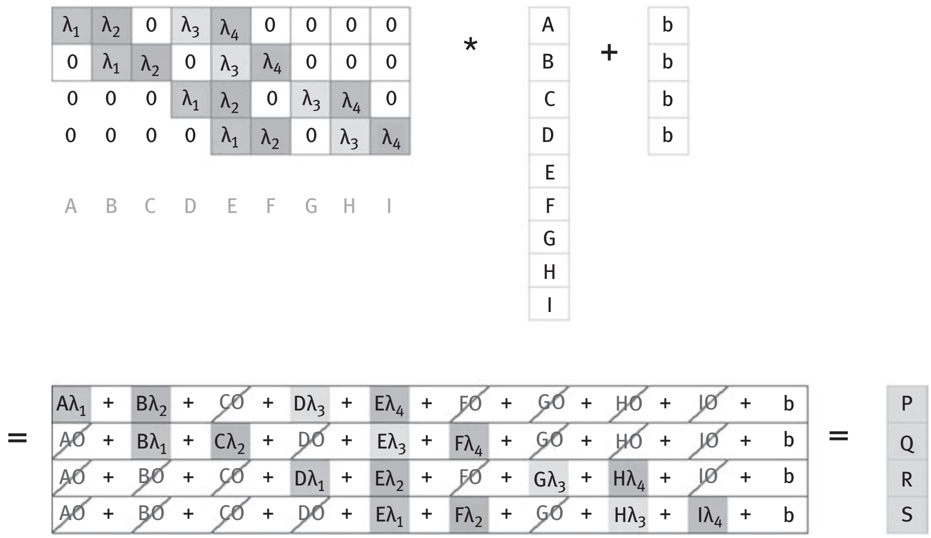


Figure 16.5: Matrix multiplication.

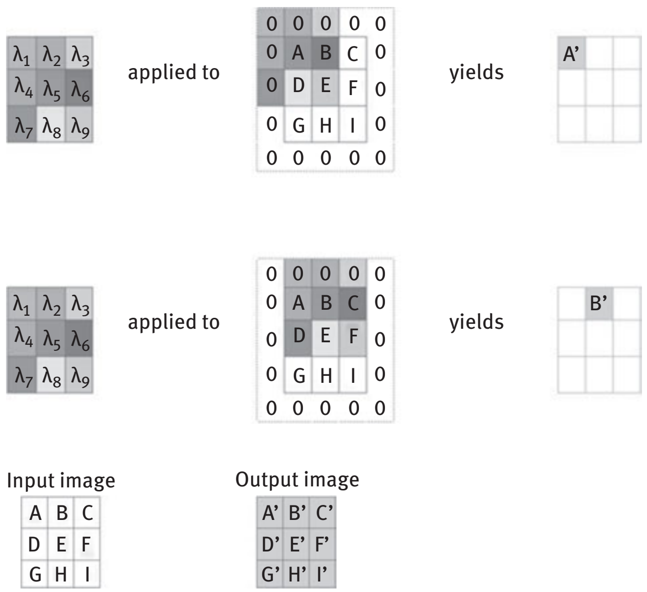


Figure 16.6: (a) Convolutional layer multiplication and (b) convolutional layer output.

16.4.3.2 Pooling layers

The next building block of ConvNet is a pooling layer. Pooling layers decrease the size of data spatially that reduces the computational effort. It does that by merging the output values of neurons in one layer into one neuron of the consequent layer.

An approach of pooling block is to downsample the feature maps by abridging the presence of features in the feature map. Two common types of pooling are average pooling and max pooling. Average pooling computes the average of all the values from the patch of the image enveloped by the filter. Max pooling returns the maximum value from the patch of the image enveloped by the feature map. Figure 16.7 depicts the concept further.

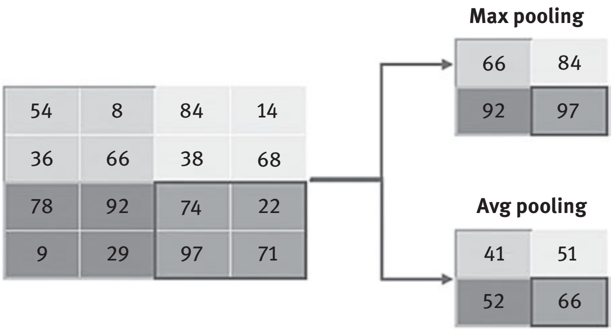


Figure 16.7: Pooling layers.

16.4.3.3 Fully connected layers

The CNN process goes through convolution and pooling layers, which breaks down the image into features. The outputs from these previous layers are flattened and advanced into FC layers that drive the final classification decision. The FC layers are basically a feed-forward neural network. In the end, softmax activation function is used to get the probability of the image being in particular class. Figure 16.8 shows the complete CNN architecture.

Number of filters, number of input channels (e.g., RGB), filter shape, and max-pooling shape are hyperparameters while developing a CNN programming model. Combining these hyperparameters with various arrangements of building blocks of convolutional layers, RELU functions, pooling layers, and FC layers, numerous CNN architectures have been developed. Some of the popular CNNs are AlexNet, VGGNet, Inception, and ResNet.

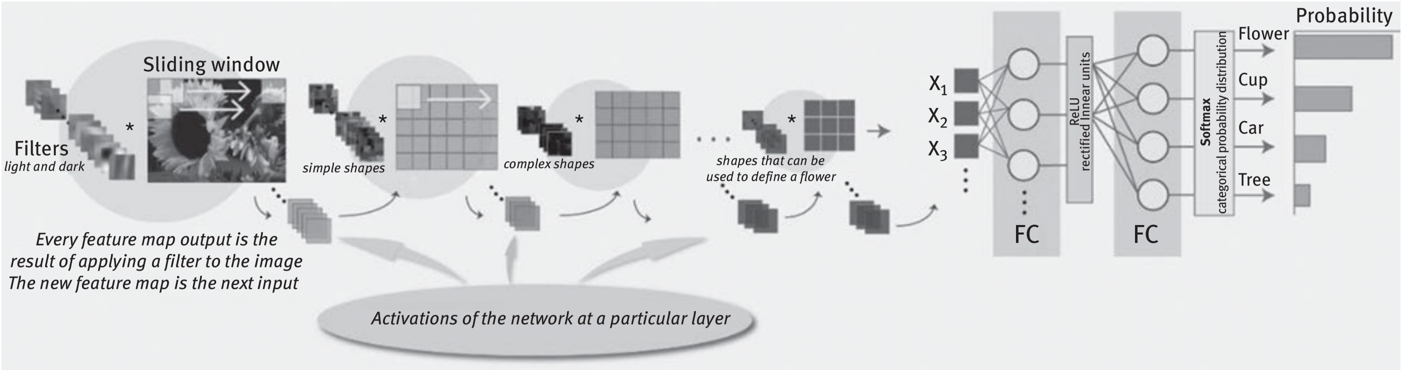


Figure 16.8: Typical CNN architecture (Sourced from Mathworks online education series).

An example of application of DL, in particularly CNNs, for plant disease detection will be discussed in the next section.

16.4.4 Practical implementation of DL in plant disease detection

Agricultural productivity is very important for every economy to thrive. Plant diseases are quite natural to occur which cause serious negative effects on yield potential of crops. As per FAO, due to cross-border plant pests and diseases, the food safety is impacted. They trigger substantial damages to farmers financially. Lately cross-border pests and diseases of plants have expanded considerably. Some of the factors for this situation are global proliferation, change of climate, and shrinking flexibility in production resulting because of agricultural escalation.

Accurate as well as precise diagnosis of diseases has been a significant challenge. Naked eye observation has been a favored method for plant disease detection. This requires a team of experts and continuous monitoring of plants, which for large farms would lead to very high costs. Also, finding and contacting proper experts is somewhat an alien concept to farmers in some countries. Plant disease diagnosis (detection) through an automated technique is advantageous as it would decrease cost and time of observing crops. One of the most effective ways can detect the disease at a very early stage, as soon as they appear on plant leaves.

Digital image acquisition has advanced, which has made image-based detection methods viable and cost-effective. Smartphones have opened door to apply innovative propositions to recognize diseases instantly because of their computing power, high-definition displays and cameras. As per an estimation, by 2020, there will be 5–6 billion smartphones in the world [14]. Although acquiring images seems to be a relatively easy task, extracting features like shape or color from the obtained image is a strenuous job that demands a procedure like preprocessing with manual expertise [15]. By using DL architecture, such as CNN, we can train an autonomous system to learn the most suitable feature without manual feature extraction.

To build a plant disease detection model, we need a large dataset. We are going to develop and discuss a DL model on the largest publicly available dataset called PlantVillage [16]. This dataset consists of 54,305 images with 14 plant species and 26 diseases. Large dataset and high-end computation power are usual prerequisites of training a new neural network-based model from scratch.

To counter these constraints, we devise the following approach. (a) Instead of constructing and preprocessing a new dataset, which can be a massive task in itself, we would leverage such publicly available dataset to establish capabilities of DL for detection of plant disease. (b) Since the purpose is to demonstrate the ease of implementation, transfer learning technique shall be used, where we build on top of an existing, well-trained network and adept it to achieve our goal of plant disease detection at minimal effort.

16.4.4.1 Transfer learning

Recently, transfer learning has become a widely employed technique in ML applications. The basic idea of transfer learning is to benefit from the models that have been trained on some task to speed up the development process on fresh similar task. In recent years, it has gained popularity in DL field because of its capability to train a DL model with comparatively lesser amount of data and in lesser time. Main intension of transfer learning is to train a model, for example, image classification, on a huge, generic, and diverse dataset such as ImageNet, can be efficiently generalized for the other computer vision problems. By availing these generic models and their feature learnings, we can commence training of a new model with moderate amount of dataset.

Typical neural networks approach is edge detection in the earlier layers, detect shapes in the middle layer, and certain distinct features in the last layers. In transfer learning, we maintain the early as well as middle layers unbothered and we only retrain the later layers at top. A new model can be developed by two transfer learning customizations: feature extraction and fine-tuning (TensorFlow (TF) transfer learning tutorial [17]).

16.4.4.1.1 Feature extraction

Let us say we want to build an image classification model on a new set of images. With transfer learning concept, we can start with a pretrained model, also called base. This base consists of features that are learnt on significantly large dataset and represents general image classification features that can help with extracting features of new image dataset without training. However, we cannot use the final top layers of the base model, because they are trained to classify certain image classes only. So, we add a new set of neural net layers on top, which will be trained for learning features specific to new set of images only. In such a situation we don't need it Train the full model from scratch, but we keep learning as the base model and just train top. In this way, we do not need to train the complete model from scratch, but we keep learning of the base model as it is and just train the top. This approach should be applied when we have relatively smaller dataset.

16.4.4.1.2 Fine-tuning

Furthermore, when we have sufficient amount of dataset and we want to have more accurate and precise image classification model, we can apply an approach called fine-tuning. To fine-tune the model, first, the top layers of base model are unfrozen. Now we train the top layers of the pretrained model and the new set of neural network layers together. This technique makes higher-order features of the base model more helpful for the particular task of classification at hand.

In this chapter, we are going to develop a plant disease classifier using pretrained CNN called ResNet-50, short for residual network with 50 layers, on ImageNet dataset.

16.4.4.2 ResNet-50

After 2013, to attain high accuracy values, the trend of building deeper networks had started. Furthermore, deeper networks are able to deal with features that are complicated. However, with building networks with more layers, the problem of vanishing/exploding gradients had come into play. Although this problem was largely handled by normalized initialization layers and enabled networks with tens of layers to converge, when DNNs start converging, it led to another problem of degrading accuracy. Hence, appending more layers in the network saturated the accuracy value. Additionally, overfitting was not the culprit for this situation.

Unexpectedly, more layers in an apt deep model increases the training error (see Figure 16.9).

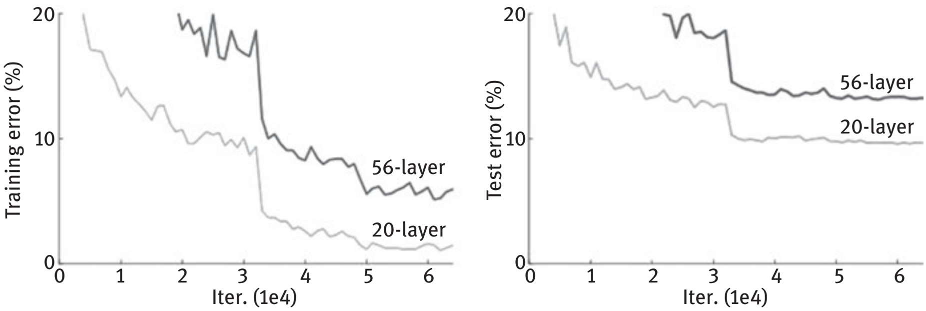


Figure 16.9: Training (left) and test (right) error with 20-layer and 56-layer neural networks on CIFAR-10 dataset [18].

To tackle this issue, Microsoft developed a framework of DL ResNet [18]. This network is more or less equivalent to CNNs consisting of layers like convolution, pooling, activation, and FC. ResNet introduced skip connection.This was carried out with the help of the identity connection between the layers. In addition to layer stacking, the output of the building (convolution) block is appended with the initial input. Figure 16.10 shows the residual block with x identity connection stemming from input connection, green skip arrow, and being added to the end in ReLU activation.

The purpose of identity connection is to enable the layers to fit residual mapping instead of skipping some stacked layers in search of suitable mapping. $f(x) + x$ can be understood as feed-forward neural networks having bypass connections. This approach has been proven successful to solve vanishing gradient problem and ensure that the higher layer would perform at least equally to the lower layer with identity mapping from input. Refer He et al. [18] to see more comparison and details on different versions of ResNet (ResNet-18, 34, 101, and 152).

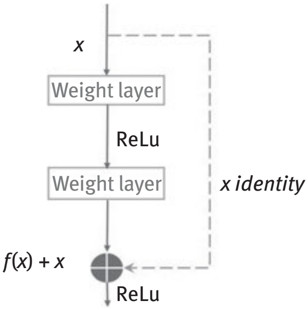


Figure 16.10: Residual building block.

Some key features of ResNet are:
– Batch normalization regulates the input to amplify network operation
– Identity connection solves the problem of vanishing gradient
– Bottleneck residual block enhances the functioning of the network

16.4.4.3 Example

As mentioned earlier, we will demonstrate an example of DL classifier developed on PlantVillage dataset in Table 16.1. The dataset contains 38 plant–disease pairs.

Figure 16.11 shows few sample of plant–disease leaf images, which are our class labels that are to be predicted by our trained CNN classifier.

In this chapter, we explore the following approaches to build our plant disease detection classifier:

I. Experiment with different train–test split of dataset:
   A. 80–20, where 80% data are used to train CNN classifier – 20% reserved for validation
   B. 60–40, where 60% data are used to train CNN classifier – 40% reserved for validation
II. Use pretrained DL architecture ResNet-50 (on ImageNet dataset) for both train–test split scenarios
III. Evaluation of the model with metrics accuracy, precision, recall, and F1 score
IV. Demonstrate application of latest DL models which can implemented on the devices having low computational power like mobile phone and Raspberry Pi and give high enough accuracy

16.4.4.3.1 Plant disease classification model with 80–20 train–test split

To develop the plant disease detector for both train–test split cases, well-known ML/DL libraries, PyTorch, and fast.ai are used. All the models have been trained on

Table 16.1: PlantVillage dataset.

Plant	Condition	Samples
Apple	Apple scab	630
Peach	Bacterial spot	2,297
Bell pepper	Bacterial spot	997
Tomato	Bacterial spot	2,127
Apple	Black rot	621
Grape	Black rot	1,180
Apple	Cedar apple rust	275
Corn (maize)	*Cercospora* leaf spot (gray leaf spot)	513
Corn (maize)	Common rust	1,192
Potato	Early blight	1,000
Tomato	Early blight	1,000
Grape	Esca (black measles)	1,383
Orange	Haunglongbing (citrus greening)	5,507
Apple	H	1,645
Blueberry	H	1,502
Cherry (including sour)	H	854
Corn (maize)	H	1,162
Grape	H	423
Peach	H	360
Bell pepper	H	1,478
Potato	H	152
Raspberry	H	371
Soybean	H	5,090
Strawberry	H	456
Tomato	H	1,591
Potato	Late blight	1,000
Tomato	Late blight	1,909
Grape	Leaf blight (isariopsis leaf spot)	1,076
Tomato	Leaf mold	952
Strawberry	Leaf scorch	1,109
Corn (maize)	Northern leaf blight	985
Cherry (including sour)	Powdery mildew	1,052
Squash	Powdery mildew	1,835
Tomato	Septoria leaf spot	1,771
Tomato	Spider mites (two-spotted spider mite)	1,676
Tomato	Target spot	1,404
Tomato	Tomato mosaic virus	373
Tomato	Tomato yellow leaf curl virus	5,357
Total		**54,305**

“H” denotes healthy samples.

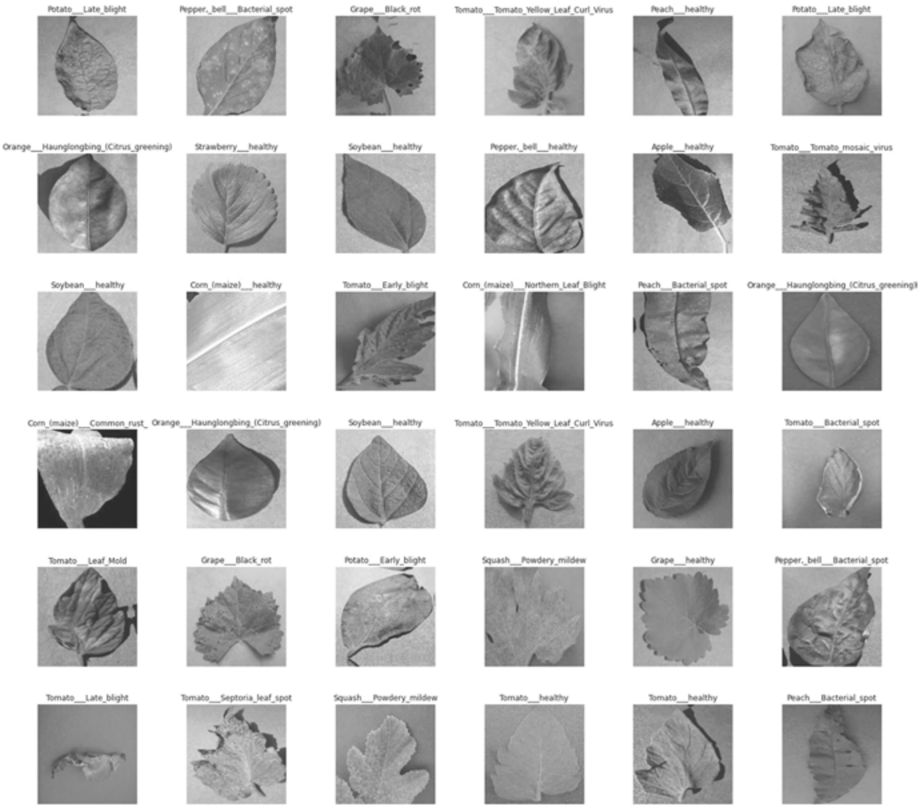


Figure 16.11: Few sample images of crop–disease pair.

free GPU computational resource in Google Colaboratory. In both train–test cases, modeling has been carried out by ResNet-50 with ImageNet weights and transfer learning. Splitting the data in 80–20 gives train dataset with 43,444 images and 10,861 images in validation dataset.

Data augmentation is one of the most frequently used regularization methods, especially common in image processing tasks. Every ML/DL model should ensure that the trained model is able to generalize to real-world data. Overfitting is modeling error where your model just learns to recognize features inside of your training dataset and does not generalize properly to carry out operation as intended on unseen set of images. To counter this, we apply different augmentations to training dataset images. Some of the common augmentations, also called transforms, are flip, rotate, crop, zoom, warp, and brightness. Here, the default augmentations and their values from fast.ai library are considered.

All the images resized to 299 × 299 with the batch size (number of training examples utilized in one iteration) of 64 are normalized as per ImageNet statistics (mean and standard deviation). Central goal of building a successful ML/DL model is to minimize loss function as much as possible. The algorithm performance is evaluated by the loss function. If the loss function outputs higher number, the predictions are inaccurate. Lower the output value, better the predictions. Manipulating the hyperparameters with an optimizer algorithm in a CNN can lead the way to further improve your model.

One of the most important hyperparameter is learning rate (LR). The LR in an optimization algorithm determines the step size at each iteration while converging to a minimum of a loss function. LR is a crucial parameter that is not easy to select. LR with too small value would lead to longer trainings, on other hand a large LR may end up in huge error or an unstable training process. Optimization algorithms are designed to guide training neural network in right direction to reduce the loss function.

To minimize the loss function, we begin by tweaking the parameters (weights) of our model. Gradients are partial derivatives that represent the effect of small change of weights on the lost function. LR is multiplied with gradients to ensure appropriate changes in weights. Some of the well-known optimizers are stochastic gradient decent, Adagrad, RMSprop, and Adam.

In present example, Adam [19] optimizer implementation in fast.ai library. Over the last few years, Leslie Smith has presented a series of papers [20–22], which has led to conception of one-cycle policy for determining apt LR. This approach has been remarkably successful in reducing training iterations and time. We will apply fast.ai implementation of this method.

For evaluation, the following metrics are computed:

$$\text{accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{TN} + \text{FN})}$$

$$\text{recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})}$$

$$\text{precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})}$$

$$\text{F1} = 2^{*}\,\frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}}$$

TP represents the number of true positives, TN the true negatives, FP the false positives, and FN the false negatives.

As discussed earlier in transfer learning, the convolutional layers that are pretrained on ImageNet are retained with their weights. We implement ResNet-50 as a base/pretrained model. We focus first on the last convolutional layers (here called head) which are meant to extract features in the image.

The model is trained in two phases: first, we begin with freezing the pretrained weights and only train the last convolutional layers at the top to transform the extracted features into probabilities for our plant disease images. Afterward, to fine-tune the model, if required, a few layers of the pretrained model are unfrozen sequentially and model is trained jointly with head using differential LRs.

In the first phase, the classifier is trained for five epochs (single epoch is a single run of the whole dataset in the neural network that includes both forward and backward propagation). The head here is defined by a convolution layer by default, in addition to that adaptive pooling layer, flatten layer and blocks of batch normalization, dropout, and ReLU layers. Batch normalization mitigates a phenomenon called internal covariate shift [23].

Batch normalization is a technique to normalize the output of a preceding activation layer by subtracting the batch mean and dividing by the batch standard deviation. Additionally, it enables the network to train with higher LR and to reduce overfitting by regularization. Dropout [24] is a computationally inexpensive and effective regularization method. In dropout, while training, we neglect neurons from particular set of neurons. The selection of neurons is an arbitrary process. Each training phase drops neurons with probability $1-p$ or neurons in the net with probability p are kept. This produces scaled-down network. Usually, dropout probability value is set at 0.5.

Table 16.2 lists the evaluation metrics for test set through the first phase. From the values of accuracy, precision, recall, and F1, we can see that model is able to perform remarkably on validation set, proving successful application of DL.

Table 16.2: Evaluation metrics for the first five epochs with frozen layers.

Epoch	Train loss	Valid loss	Accuracy	Precision	Recall	F1
0	0.229193	0.118834	0.961974	0.965092	0.961974	0.961375
1	0.141339	0.058804	0.982506	0.983543	0.982506	0.982226
2	0.064718	0.028649	0.991161	0.991337	0.991161	0.991138
3	0.039424	0.016432	0.994476	0.994491	0.994476	0.994475
4	0.027695	0.015430	0.995212	0.995248	0.995212	0.995200

Although this is already state-of-the-art accuracy, let us try to amend the model to perform better. In order to do so, first, we use a functionality called LR finder. This functionality, which is based on cyclic learning [20], helps in finding best LR values or range of efficient training.

We unfreeze few of the layers on the top of the body and now the model is trained on those layers in addition to the head. This helps minimize loss further. LR is chosen to be in the range of ($1e-6, 1e-4$) from Figure 16.12. Please refer the fast.ai library documentation to know how to select these LR. For five more epochs, we obtain evaluation metric values as shown in Table 16.3.

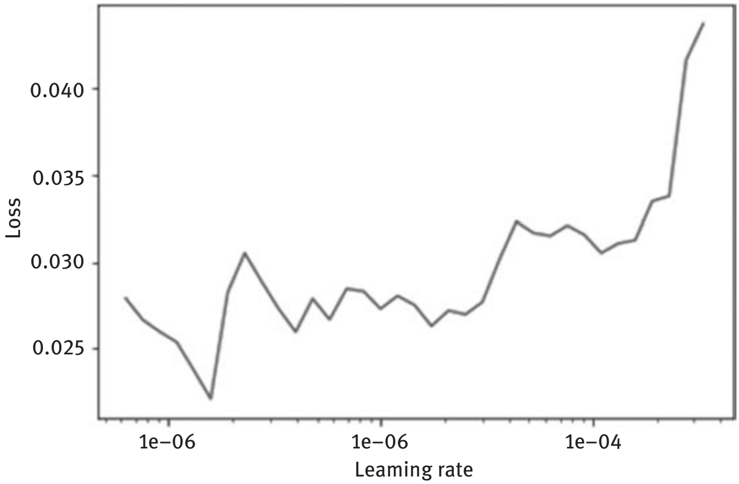


Figure 16.12: LR finder plot.

Table 16.3: Evaluation metrics for five epochs with unfrozen layers.

Epoch	Train loss	Valid loss	Accuracy	Precision	Recall	F1
0	0.017772	0.015000	0.995396	0.995444	0.995396	0.995391
1	0.022458	0.013348	0.995673	0.995703	0.995673	0.995670
2	0.014861	0.012323	0.996133	0.996177	0.996133	0.996120
3	0.007548	0.010475	0.996593	0.996614	0.996593	0.996588
4	0.009854	0.009361	0.996870	0.996883	0.996870	0.996867

The values of metrics have refined little more; however, one should always take into consideration the computational effort spent against the improvement gained. As shown in Figure 16.13, we plot some of the wrongly classified labels. These are some of the predictions with highest lost values resulting in wrong classification. However, here, if we notice, the first and second images are not leaf images.

Thus, it is necessary to verify and remove such anomalies from the data to build a better classifier. Furthermore, Figure 16.14 depicts the confusion matrix of plant disease leaf images of validation dataset. The confusion matrix plots actual against predicted labels. Number of images on diagonal shows correctly predicted label of plant–disease pair.

At last, we analyze the plant–disease labels which get confused with each other. We find out that classifier got confused six times while predicting if the label is corn gray leaf spot or corn northern leaf blight, four times between tomato early blight and tomato late blight, and three times between potato late blight and

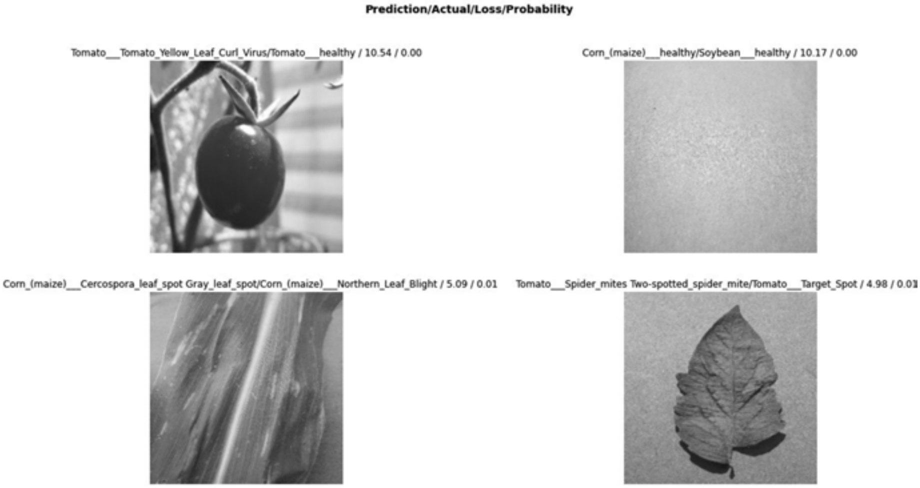


Figure 16.13: Wrongly predicted labels.

tomato late blight. One solution to make classifier perform better on these labels is to include a greater number of images for these categories.

16.4.4.3.2 Plant disease classification model with 60–40 train–test split

All the steps of process discussed in 80–20 are repeated with 60–40 train–test split as well. Train and test datasets have 32,585 and 21,720 leaf images, respectively.

In the first phase of training, the classifier with five epochs yields the metric values in Table 16.4.

Classification model with 60–40 split produces almost as good values as 80–20 split. However, the computational effort required to train the 60–40 model will be appreciably lesser than 80–20.

When the classifier is trained further with unfrozen layers and LR (1*e*–6,1*e*–4), we attain almost similar metric values (see Table 16.5). Although there is a possibility of overfitting in this model, it is apparent that even with lesser number of epochs and training data size, the results of 60–40 split would be sufficient to put the trained model into real-time application. Let us see confusion matrix plot and some of the incorrect classified labels.

Figures 16.15 and 16.16 demonstrate the similar outcome as 80–20 dataset. Most confused predicted labels are corn gray leaf spot versus corn northern leaf blight (13 times), tomato early blight versus tomato late blight (4 times), and potato late blight versus tomato late blight (3 times).

We can conclude from the above two cases (80–20 and 60–40) that DL architectures are easy to implement, and we can train a model for supervised data without

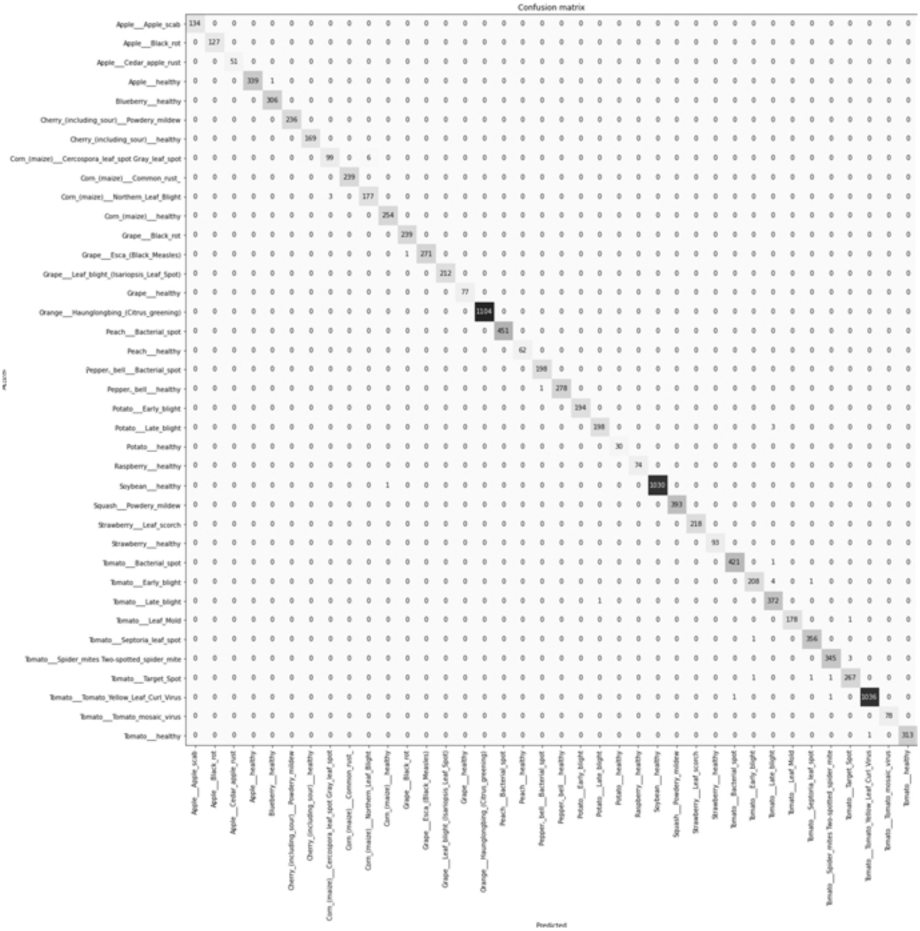


Figure 16.14: Confusion matrix.

Table 16.4: Evaluation metrics for the first five epochs with frozen layers (60–40 split).

Epoch	Train loss	Valid loss	Accuracy	Precision	Recall	F1
0	0.261387	0.111309	0.964871	0.966246	0.964871	0.964640
1	0.140933	0.052491	0.983564	0.984011	0.983563	0.983526
2	0.078067	0.040790	0.986924	0.987154	0.986924	0.986861
3	0.038494	0.025079	0.992403	0.992717	0.992403	0.992391
4	0.028228	0.020121	0.993646	0.993631	0.993647	0.993630

Table 16.5: Evaluation metrics for five epochs with unfrozen layers (60–40 split).

Epoch	Train loss	Valid loss	Accuracy	Precision	Recall	F1
0	0.024634	0.020507	0.993462	0.993552	0.993462	0.993459
1	0.021005	0.016001	0.994843	0.994853	0.994844	0.994840
2	0.021123	0.013734	0.995764	0.995788	0.995764	0.995764
3	0.013197	0.012448	0.996317	0.996320	0.996317	0.996315
4	0.009725	0.012053	0.996823	0.996848	0.996823	0.996823

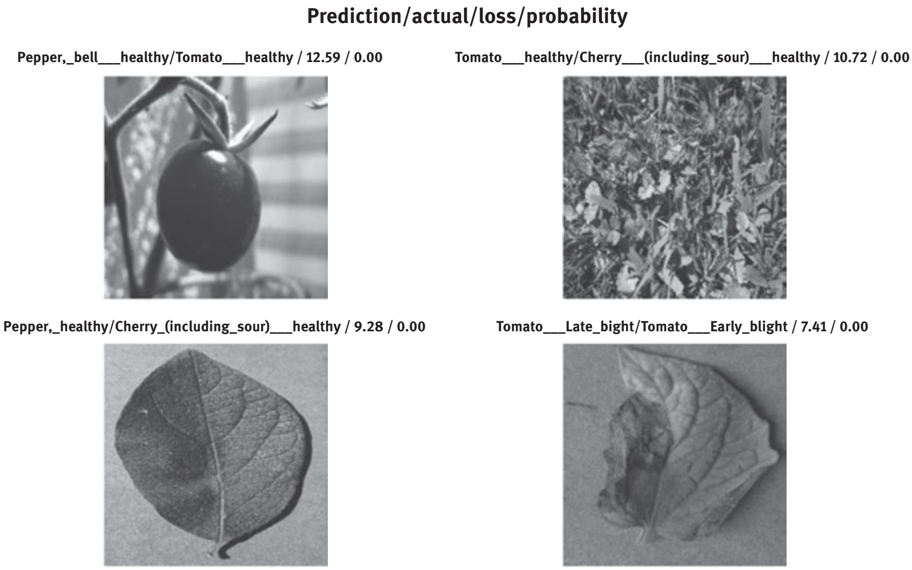


Figure 16.15: Wrongly predicted labels (60–40 split).

too much manual work. At the same time, they are capable of beating the traditional approaches by a notable margin in conventional benchmarks. Even the model trained only on 60% data (32,585) is capable of detecting plant disease with near-perfect accuracy.

The trained classifier can further be used in a web or a mobile application (as shown in Figure 16.17), where it can predict the plant disease within a second.

In the next step, we will experiment with the application of latest DL models that are made especially for IoT edge devices.

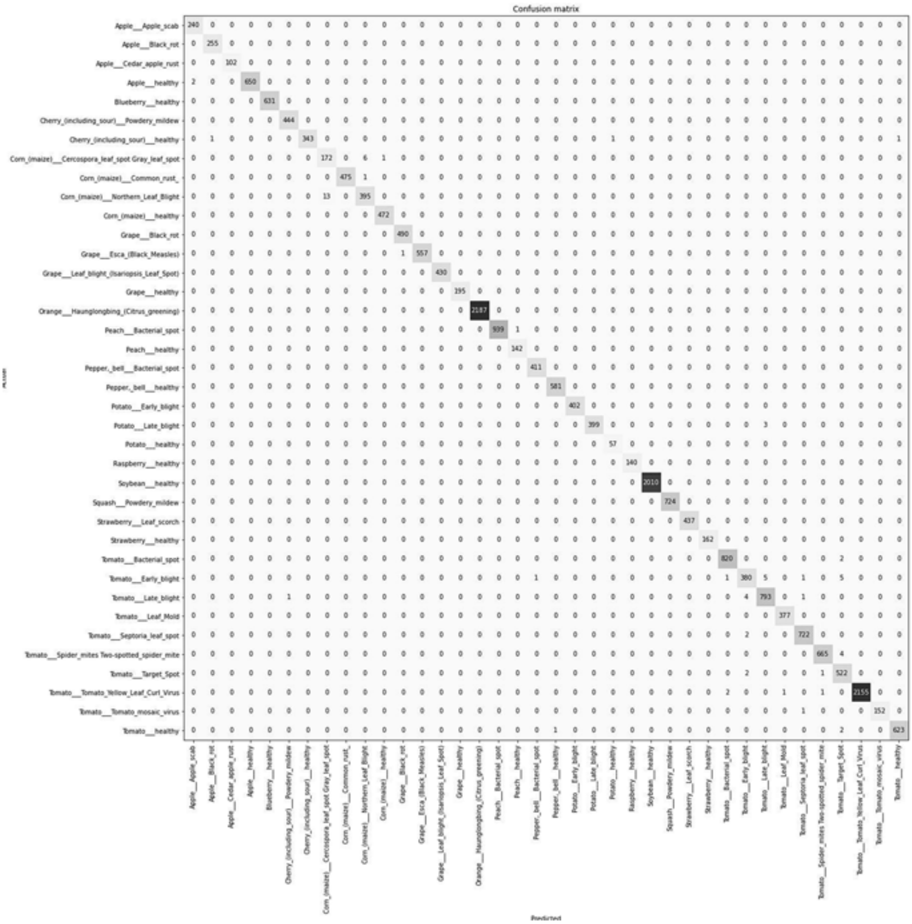
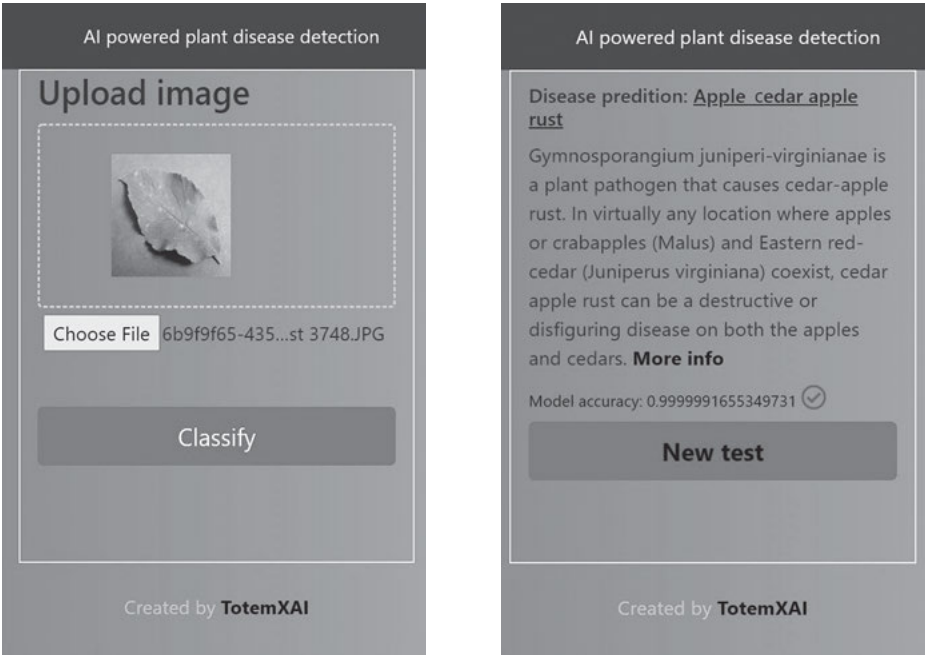


Figure 16.16: Confusion matrix (60–40 split).

16.4.4.3.3 DL models for IoT edge devices

Cloud computing is a powerful resource system for storage and processing, but they tend to create delays for IoT devices sending data back and forth. IoT edge devices can solve this fundamental problem associated with cloud architecture by bringing cloud computing capabilities to local devices. IoT edge computing devices are competent to process data rapidly, avoid delays, faster decision making, and most importantly address the security concern. Running ML and DL models directly on IoT edge devices reduces the latency with no need of sending the data to the cloud to realize AI capabilities. Renowned chip manufacturers such as Qualcomm, NVIDIA, and ARM have launched dedicated chips to execute AI-enabled applications in the last couple of years.



(a) (b)

Figure 16.17: (a) Web app – plant disease detection. (b) Web app – plant disease detection.

ML/DL with edge computing has a primary goal to move the inference part of the AI workflow to the device. It becomes crucial to have lowest possible latency in application like autonomous driving, which is possible by ML/DL model deployed on edge device in the car. AI processing on the edge is also playing an important role in advanced area of research such as federated learning and blockchain-based decentralized AI architectures by carrying out some part of model training the edge device only. Some of the popular AI–IoT edge devices are Raspberry Pi 4, NVIDIA Jetson, Intel Neural Compute Stick 2, and Google's Coral dev board.

Google has developed a lightweight framework of TF called TF Lite that is designed to help with inference of TF models on devices with low computational power. TF Lite converted models have low latency and a small model sizes which empower devices such as mobile, embedded, and IoT devices to run ML inference on the edge. In March 2020, Google released image classification model called EfficientNet-Lite, which runs on TF Lite. EfficientNet-Lite models, derived from the bigger version EfficientNet [25] published in 2019, are specifically designed for performing on low computational resources such as edge devices.

Figures 16.18 and 16.19 show how the available variants of EfficientNet-Lite perform, for low latency and small model size option (EfficientNet-Lite0) to the higher accuracy alternative (EfficientNet-Lite4), compared with other popular DL models on ImageNet dataset. Quantized version of the respective models [26] was run on Pixel 4 smartphone CPU having four threads and results were observed. Quantization can be defined as a technique that transforms the model to have smaller size and simultaneously boosting latency of hardware at an expense of minimal loss.

We assessed a quick implementation of EfficientNet-Lite with a tool developed by Google for transfer learning, called TF Lite Model Maker. This model was trained for 80–20 train–test split with the default hyperparameters using pretrained EfficientNet-lite0. At the end of five epochs, model produces 96.30% accuracy on test dataset that should improve with training for higher number of epochs. Although this accuracy is somewhat lower than what we obtained for ResNet-50, it is noteworthy that the model trained with pretrained EfficientNet-lite0 has only 48,678 trainable parameters against 2,180,007 with pretrained ResNet-50. This means the training time with EfficientNet-lite0 would be significantly less.

Moreover, in the present case, the model has a size of only 13 MB, which would occupy much lesser space on an edge device and evidently the inference (latency) speed would be swift. If a classifier with the little degraded accuracy is acceptable, a significant amount of computational and hardware cost can be saved. Additionally, there is a possibility of utilizing this model offline too with low-powered computational device. So, in rural areas, where there may be difficult to have steady Internet (cloud) connectivity, we can deploy such a small-sized model on a moderately resourced edge device.

In the discussed example, we developed a plant disease classifier on plant leaf images with the aim of detecting and recognizing plant categories and associated diseases. Evaluation metric results prove that precise classification of all the 38 classes of crops and diseases is attainable without applying any expert feature engineering nearly all the time. Although training such classifier is computationally intensive, for inferencing (predicting for an image in real time), it can easily run on a smartphone. Moreover, we can build computationally cheap and efficient model to deploy on IoT edge devices.

Although we are able to attain state-of-the-art accuracy, the dataset (only publicly available large dataset on plant disease) in the consideration in present example is prepared under well-curated lab conditions. Due to this reason, the model trained may perform poorly on real-life leaf images. Obvious approach would be collecting more plant disease leaf images from real-life scenarios and build a classifier on that. However, this approach is very time consuming and cumbersome. A recently published dataset PlantDoc [27], which is developed with roughly 300 manual hours of effort to annotate the images scraped from Internet, includes 13 plant categories with 2,598 plant leaf images and up to 17 disease classes.

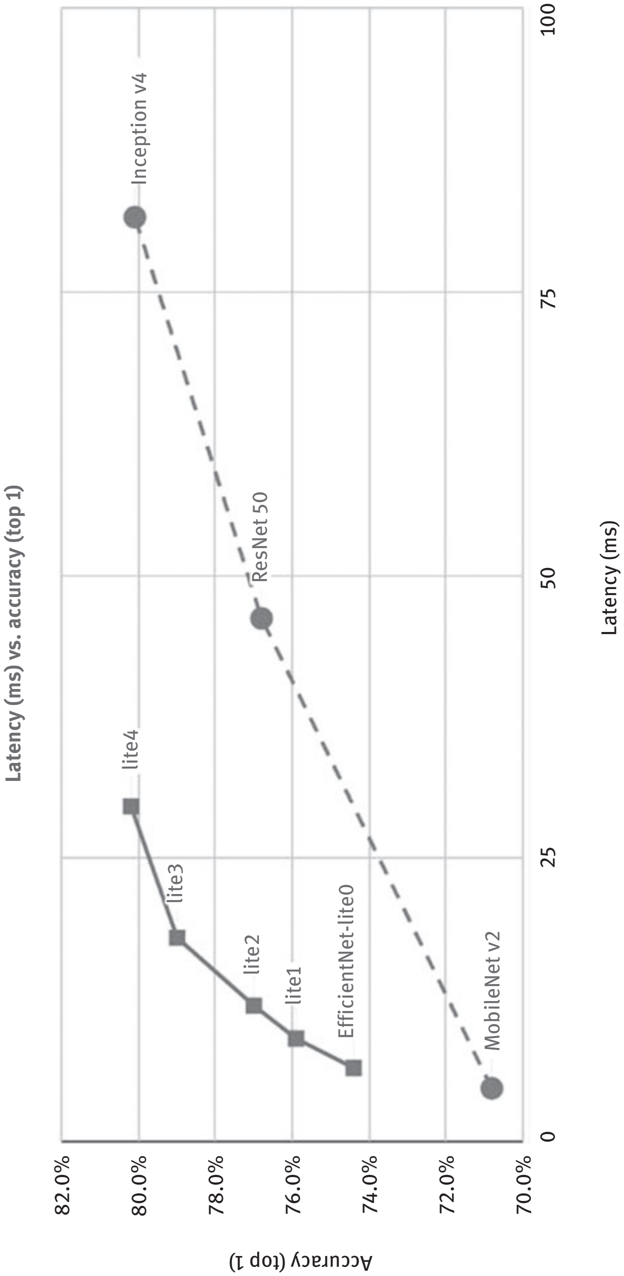


Figure 16.18: Latency of EfficientNet-lite versus other quantized models [26].

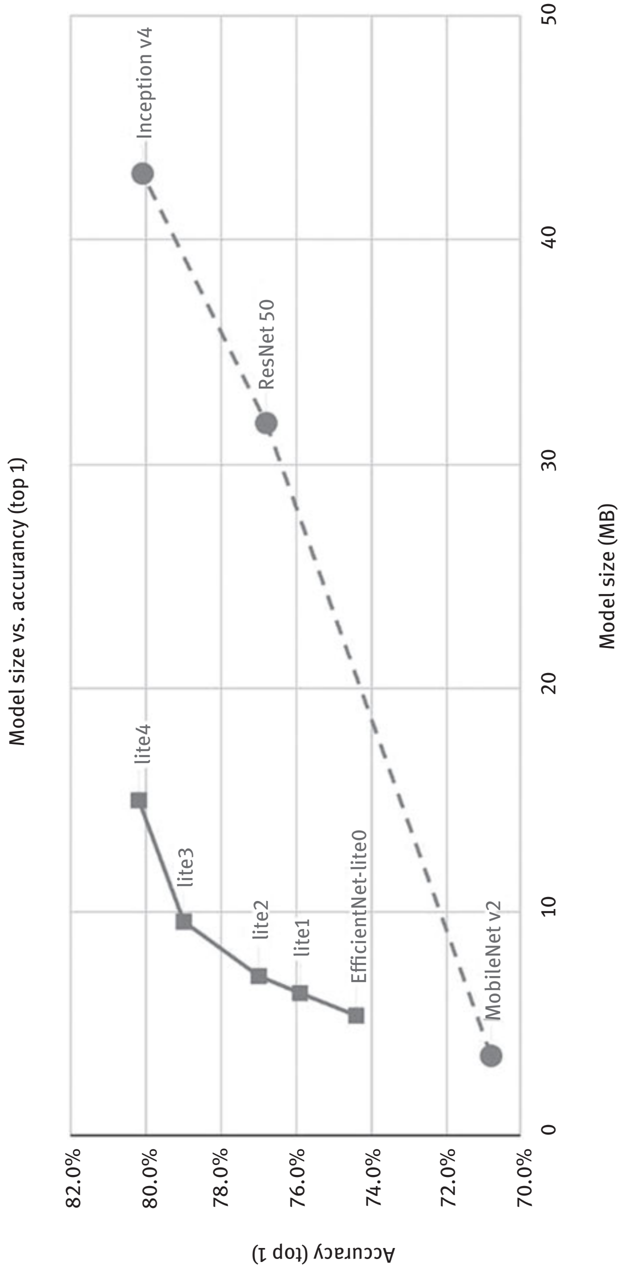


Figure 16.19: Model size of EfficientNet-lite versus other quantized models [26].

It is claimed that the classifier trained on this dataset performs better than PlantVillage in real time; the all-over accuracy of the model is around 60% only. This means that we need more images for each label (plant–disease pair) to develop a deployable DL classifier. One way to deal with this is using a technique called semisupervised learning. Semisupervised learning is a novel concept that combines supervised and unsupervised learning by taking both labeled and unlabeled data to train a model with majority of unlabeled data points. Lastly, plant leaf dataset with bounding boxes (image/object detection) around the disease affected area in images can give better representation for crop disease detection.

16.5 Conclusion

The critical global requirement of efficient and effective plant disease detection is acknowledged. By reviewing the current diagnosis methods, the shortcomings are identified. As an alternative, theoretical and practical implementation of DL is discussed stepwise.

It is evident from the clear conceptual overview of current application that DL in agriculture has very prominent present and future with application such as plant disease detection. DL can help cut down significant amount of time and efforts for plant disease detection. Moreover, with concrete example demonstrated, it is apparent that DL model can bring significant accuracy and efficiency which can outperform visual human inspection.

The chapter also denotes cost-effectiveness and ease of implementation of DL models, encouraging employment of modern technology such as IoT and DL in agritech. DL is changing dynamics of all the major industries and shows a strong promise to revolutionize the field of agriculture with DL.

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17 Using deep learning for image-based plant disease detection

Abstract: Crop ailments pose a great threat to us. Crops are a major source of nutrition in the world. It is usually very hard to identify and analyze ailments in a crop through the naked eye. In this chapter, we discuss how different deep learning and machine learning techniques can be used to identify and analyze crop aliments with high accuracy.

Keywords: Deep learning, disease detection, smart farming

17.1 Introduction

17.1.1 Machine learning and deep learning

The term "machine learning" was initially used in 1959 when Arthur Samuel [1] worked to demonstrate that a computer could be programmed to learn to play a game of checkers better than the person who wrote the original program. Arthur Samuel defined machine learning as "the field of study that gives computers the ability to learn without being explicitly programmed." Over time, various different definitions and categorizations of machine learning systems and tasks have been suggested.

Goodfellow et al., in their book *Deep Learning* [2], refer to machine learning as the capability of artificial intelligence (AI) systems "to acquire their own knowledge, by extracting patterns from raw data." In the introduction to the book, *Machine Learning* [3], Tom M. Mitchell suggests the following formal definition: "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E." Computer programs and AI systems then leverage this knowledge to perform a variety of tasks, such as recognizing handwritten digits, classifying an email as spam or not, detecting fraudulent financial transactions in real-time, customized product recommendation on an e-commerce website, and translating texts between different languages.

The goal of a machine learning system is to learn from historical data for optimizing a model in order to perform well on unseen data. The main input of our machine learning system is a collection of historical or real-time data that can be

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https://doi.org/10.1515/9783110691276-017

structured or unstructured, and is referred to as the dataset. The model can be thought of as a black box that contains a number of parameters and can map instances from the input space to the output space.

Deep learning is a subdivision of machine learning which emphasizes on learning consecutive layers of progressively more and more meaningful representations. The deep in deep learning stands for this idea. Yan LeCunn et al., in the quintessential paper, Deep Learning [4], state that – "Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction." Deep learning models from the input progressively extract more and more sophisticated level features. In image processing, for example, while the lower layers may identify just edges, the higher layers may identify the concepts such as digits or faces that are relevant to humans. Some applications of deep learning include speech recognition, drug discovery and toxicology, recommendation systems, customer relationship management, and financial fraud detection.

Deep learning allows algorithmic frameworks which are made out of various processing layers to grasp the depiction with numerous degrees of abstraction of data, speech identification, and object recognition and identification. Deep learning has applications in various diverse areas such as drug discovery and genomics as well. Deep learning finds multifaceted configurations in enormous data indexes by employing the backpropagation calculation to exhibit how a machine should alter its inner specifications that are utilized to figure the depiction in each layer from the depiction in the past layer.

Deep learning cannot exclusively can create valuable outcomes where different techniques come up short, yet additionally can assemble more exact models than different strategies, and can lessen the time expected to manufacture a helpful model. Be that as it may, preparing deep learning models requires a lot of processing power. The main attribute for deep learning is that the model being prepared has more than one concealed layer between the input and the yield.

17.1.2 Plant diseases

Crop diseases are a significant danger [5] to food security; however, their fast-distinguishing proof stays troublesome in numerous parts of the world because of the absence of the fundamental infrastructure. In general, a plant becomes infected when it is ceaselessly upset by some causal agent that results in a strange physiological procedure that interrupts the plant's usual configuration, development, work, or various activities. Infectious plant ailments are brought about by living (biotic) agents, or pathogens.

These pathogens can be diffused from a contaminated plant or plant debris to a good plant. Microbes that are responsible for plant diseases incorporate nematodes, fungi, bacteria, and mycoplasmas.

17.1.3 Plant disease detection

Exact and accurate detection of plant diseases has been a significant challenge. Customarily, the detection of plant infections has depended on human explanation by visual assessment. But with the recent advancement in technology, new techniques and algorithms have been discovered which are able to detect plant diseases accurately and within a short period of time. Deep learning with convolutional neural networks (CNNs) [6] has made incredible progress in the classification of different plant diseases. Deep neural networks have, as of late, been effectively applied in numerous assorted spaces as instances of learning end to end.

Neural networks give a mapping among an input, for example, the image of an unhealthy plant to an output, for example, a pair of crop disease. Nodes in a neural network are algebraic functions that take numeric contributions from the approaching edges and give a numeric yield as an outgoing edge. So, in order to create an accurate plant disease classifier, we need a huge established data index of the images of ailing and well plants.

17.1.4 Image-based detection/classification

Image characterization alludes to a procedure in computer vision that can categorize images as indicated by their visual substance. An image classification algorithm might be intended to predict if a picture has a human figure or not. Grouping of objects is an utterly easy assignment for humans, yet it has ended up being a difficult one for machines and therefore image classification has been an important job within the domain of computer vision. Image classification refers to the naming of images into one of the numerous preestablished classes.

There is a conceivable quantity of classes into which a given image can be classified. Manually checking and characterizing images could be a repetitive assignment especially if they are monstrous in quantity (say 200,000) and hence, it will be extremely valuable in this case that we could mechanize this entire process by utilizing computer vision.

17.2 Steps involved in using deep learning for image-based plant disease detection

17.2.1 Commonly used steps

17.2.1.1 Dataset collection

Proper data indexes are necessary for any phase of beholding research, ranging from the training stage to the evaluation of the performance of the detection algorithm. Images are often accumulated onsite or online.

17.2.1.2 Image preprocessing and labeling

So as to impulse the improvement of feature extraction, the final images that are supposed to be utilized as a dataset for neural network classifiers [7] should be preprocessed to realize constancy. Moreover, the image preprocessing procedure must involve cropping of photographs by hand, making a square around the infected area, so as to focus on the region of interest.

17.2.1.3 Image augmentation

The reason for utilizing augmentation is to extend the dataset and acquaint little bit of contortion to all of the images that helps in diminishing overfitting while the training phase. Overfitting occurs if a model describes error or arbitrary noise instead of underlying relationships in the image [8]. The various image augmentation techniques include transformation, perspective transformation, and image rotations.

17.2.1.4 Neural network training

There are several well-known deep learning frameworks like Theano [9], Lua, and Torch [10]. Additionally, there is Caffe [11], a framework by Berkeley Vision and Learning Center, which contains pretrained Caffe models.

17.2.1.5 Performing tests

The normal methodology in estimating the accuracy of models is parting information into the training and the test sets. The accuracy of our predicted result can be easily determined as the underlying results for the testing set and our model anticipated results are known.

17.2.1.6 Fine-tuning

The purpose of fine-tuning is to expand the adequacy or proficiency of a procedure or the function by making little changes to upgrade or improve the outcome.

In addition to the abovementioned six steps, some other steps used include image segmentation and severity analysis [12].

17.2.2 Image segmentation

Image segmentation [13] means dividing the given image into several fragments having the same attributes or parts with some commonality. Segmentation can be done using different methods like boundary and spot detection algorithm and k-means clustering.

17.2.2.1 Boundary and spot detection algorithm

The given RGB (red green blue) image is first transformed into the hue saturation intensity color space for segmenting. Boundary detection [14] and spot detection facilitates the finding of the part of the image that is infected. For boundary detection, 8-pixel connectivity is considered and a boundary detection algorithm is utilized.

17.2.2.2 K-means clustering

K-means clustering groups the objects based on a particular set of attributes into k clusters. The grouping of objects is a process in which the sum of the squares of the distance among the object and the particular cluster is reduced.

17.2.3 Severity analysis of plant diseases

The severity of plant diseases is essential as it can be used to predict the yield and recommend treatment [12]. It also will help to reduce yield losses. Severity may be theorized either by the area or how intense is the affection. How deeply rooted affection is can be judged by the color and texture attributes.

So as to give a gauge to the seriousness of the disease, most evaluation algorithms initially have a division venture to segregate the side effects, from which attributes can be disengaged and handled. Various methods that are used for severity analysis of plant diseases are mentioned further.

17.2.3.1 Thresholding

Thresholding is one of the first methods and was proposed by Lindow and Webb [15]. This method has been used by various researchers for severity analysis in coffee leaf, sunflowers, and oat leaves, measuring the damage caused in leaves by spider mites, quantification of lesions in soybean leaves, and finding the extent of the fungi associated disease in sugarcane leaves.

17.2.3.2 Color analysis

Color analysis has been used for estimating the severity of eelgrass leaf injury and quantification of nitrogen deficiency in barley leaves.

17.2.3.3 Fuzzy logic

Fuzzy logic [16] has been used for quantifying the symptoms of the diseases in cucumber leaves and pumpkin in the evaluation of the degree of hopper infestation in rice crops.

17.2.3.4 Neural networks

The initial tries to observe plant fitness using neural networks was first by Hetzroni et al. [17]. The system proposed by them monitored lettuce leaves and tried to detect nitrogen, zinc, and iron absence.

17.3 Case study of various deep learning approaches used

17.3.1 Using AlexNet and GoogleNet on the PlantVillage dataset

Mohanty et al. [5] used a framework to spot 14 crop types and 26 ailments. The trained model obtained a precision of 99.35% on the holdout test index, which demonstrated the viability of this method.

17.3.2 Cassava disease detection using transfer learning

Cassava is one of the biggest sources of carbohydrates for human nutrition on this planet; however, it is at jeopardy to viral diseases that take steps to damage nourishment security in the world. Novel techniques for cassava ailment recognition are expected to help improve command which will forestall the emergency. Image recognition provides both a practical and adaptable innovation for infection classification. Recent transfer learning strategies provide a road for the innovation to be handily conveyed on cell phones.

Utilizing a data index of cassava plant diseased instances, Ramcharan et al. [18] differentiated three illnesses by employing deep convolutional neural network (DCNN) which was trained using transfer learning. On applying various models, they found out that the prime model outputs a precision of 93% for information not utilized in the training procedure. Their outcomes show that the transfer learning approach offers a quick, reasonable, and effectively deployable methodology for computerized plant diseases recognition.

17.3.3 Application of deep learning for detection of virus in potatoes using hyperspectral images

Virus illnesses are of great concern in the development of seed potatoes. When recognized in the area, infection of sick crops leads to declassification or even dismissal of the seed parts bringing about a money-related misfortune for the farmers. Farmers put in a great deal of exertion to recognize unhealthy plants and expel infection-ailing crops from the area. However, subject to the variety, infection of unhealthy crops can be overlooked during visual perceptions, specifically in a beginning period of cultivation.

Therefore, there is a requirement for quick and target illness discovery. Research facility trials in the earlier years by Polder et al. [19] indicated that hyperspectral imaging obviously could recognize solid from infection tainted potato plants. Hyperspectral pictures are captured in the area with the help of a line interim of 5 mm. A CNN was adjusted for hyperspectral pictures and prepared on two exploratory rows in the area. The prepared system was approved on two different lines with various potato cultivars. For three of the four-line/date blends, the accuracy and review contrasted with regular illness appraisal surpassed 0.78 and 0.88, separately. It demonstrates the fitness of this approach for real-time ailment recognition.

17.3.4 Cucumber diseases recognition using deep neural network

Traditional ways of identifying cucumber ailment are frequently tedious, relentless, and abstract. In order to overcome the aforementioned challenges, a DCNN was presented to analyze the cucumber and to perform identification of four cucumber ailments [20], that is, anthracnose, downy mildew, powdery mildew, and target leaf spots. The side effect examples were sectioned from cucumber leaf examples caught under farm settings. So, to diminish the possibility of overfitting, data expansion techniques were used to broaden the data index framed by the sectioned side effect examples. With the increased data index having 14,208 side effect examples, the DCNN accomplished great acknowledgement outputs, with a precision of 93.4%. So, to look at the end result of the DCNN, similar analyzes were directed utilizing regular classifiers (random forest and support vector machines (SVMs)) and AlexNet. Results demonstrated that the DCNN was a hearty apparatus for perceiving the cucumber ailments in farm condition.

17.3.5 Application of transfer learning and DCNN in rice plant diseases detection

Rice is one of the most consumed crops in the world. About 450 million metric tons of rice are consumed worldwide every year. Early and exact analysis of plant ailment is a crucial step in the yield assurance framework. In this case study [21], we are focused on rice plant diseases. The images of the infected manifestations in leaves and stems have been caught from the rice field. The dataset consists of an aggregate of 619 rice plant diseased images from the genuine field condition which belongs to four classes: rice blast, bacterial leaf blight, sheath blight, and healthy leave. In the study, an already trained model is employed as a property extractor with SVM as a classifier. Using this combination, good results were obtained. The early distinguishing proof of rice ailment by this methodology could be utilized as a preventive measure as well as an early warning framework. Furthermore, it could be stretched out to build up a rice plant infection recognition framework on genuine agribusiness field.

17.4 Deep learning advantages in plant disease detection

Crop ailment detection through the optical perception of the indications on crop leaves includes an essentially high level of multifaceted nature. Because of this unpredictability and the large number of refined crops and their current phytopathological issues, even knowledgeable agriculturalist and plant pathologists are often unsuccessful in identification of specific ailments and are consequently led to incorrect diagnosis and treatment. The presence of a computerized arithmetic framework for the location and determination of crop ailment would provide significant help to the agriculturalist who is approached to carry out such judgments through the visual perception of leaves of contaminated crops [22].

The central objective of these methodologies is to consequently recognize the diseases so as to give appropriate treatment in time [23]. Machine learning-based AI implementations have accomplished massive development, prompting the advancement of novel systems and models with the advancement of computational frameworks as of late and specifically graphical processing units embedded processors. Deep learning alludes to the utilization of artificial neural network designs that have a very huge number of processing layers rather than "swallower" models of added customary neural system procedures.

One of the major advantages of using deep neural networks [24] is that the properties relating to the diseases of the plant need not be handcrafted; the model can get familiar with the significant properties given adequate processing information. Furthermore, it can also measure the severity or intensity of the diseases from which the plant is suffering by providing the relevant data to the model.

17.4.1 Deep learning over machine learning

For all intents and purposes, deep learning is a subset of machine learning that accomplishes extraordinary power and adaptability by figuring out how to represent the world as a settled chain of importance of concepts, with every concept characterized according to a less difficult concept, and progressively dynamic portrayals processed as far as less theoretical ones.

In conventional machine learning procedures, the majority of the used factors should be recognized by a field specialist so as to decrease the randomness of the information and make designs more capable of grasping calculations.

The greatest advantage of deep learning as talked about before is that they try to grasp complex properties from data in increasing order. This removes the requirement of field experts and hardcore feature extraction. Another significant contrast between deep learning and machine learning procedure is in the approach to solve problems. Deep learning procedures will, in general, take care of the problem in an end-to-end manner, whereas machine learning methods need difficult proclamations to separate to various parts to be explained first and afterward their outcomes to be joined at a definite stage.

Machine learning also finds difficulty in analyzing unstructured data formats. Whereas deep learning is able to utilize different data formats to extract insights and train deep learning models. For example, you can utilize deep learning calculations to reveal any current relations between industry examination, online networking jabber, and more to foresee up and coming stock costs of a given association.

In machine learning, feature engineering is a major activity as it improves precision, and now and then the procedure can require domain data about a specific issue. Probably the greatest favorable position of utilizing a deep learning approach is its capacity to execute feature engineering without anyone else. In this methodology, an algorithm checks the information to distinguish features which correlate and afterward consolidate them to advance quicker learning without being advised to do so explicitly. This ability causes data researchers to spare a lot of work.

17.5 Deep learning limitations in plant disease detection

In order to get good outcomes in the identification of crop ailments, deep learning strategies need a more prominent measure of data [25]. This is a disadvantage since right now accessible data indexes are generally compact and do not have required instances, which is a need for good analysis. An exhaustive data index must have instances caught in various circumstances, however much as could reasonably be expected. One of the solutions to this problem is when there is an absence of examples in the training information, and customary methods do not improve the outcomes fundamentally, generative adversarial networks (GANs) could be utilized for creating engineered information.

Datasets that do not have ample amount samples for deep neural networks do not encourage legitimate learning of the classes. Annotation errors may also cause a disruption in the learning process. Background of the image may contain certain components that may lead to the disturbance in the training process. These elements can be a major problem if they are present in multiple samples.

In the current scenario, deep learning models have been somewhat successful in detecting plant diseases. But there is still a huge space of improvement. There are a few restrictions or confinements in this exploration area. One of them is that presently accessible data indexes do not have instances accumulated and marked from genuine circumstances. Along these lines, training is directed with instances taken in a comfortable domain. Another restriction is that as of now, the presented techniques cannot identify various illnesses in a single image or cannot distinguish different events of similar illnesses in a single image.

As shown by Mohanty et al., when a lot of test images are taken under conditions not quite the same as the pictures utilized for training, the accuracy of the model is diminished considerably, to simply above 31% from the first 99%. As images that are captured can be in a wide variety of conditions, in order to be representative, it must cover all the possible conditions, which is not feasible.

17.5.1 Overcoming limitations

A new dataset was presented by Arsenovic et al., which had images of plant leaves in genuine environmental factors, at various edges, and in different climate conditions, labeled for both classification and identification assignments. Along these lines, the data index is increasingly extensive, which enhances the classification.

A novel expansion strategy dependent on GANs and a novel two-phase calculation intended to enhance crop ailment location in genuine condition instances was implemented by Arsenovic et al., which gives quick outcomes, making it sufficient for ongoing application. To overcome the problem of simultaneous disorders, we can adopt localized symptom regions.

At last, a novel two-phase engineering, the PlantDiseaseNet, was presented for plant ailment identification. The trained model accomplished a precision of 93.67% on the PlantDisease data index, and because of its engineering structure, it ended up being effective in circumstances with complex environmental factors. Accuracy might be upgraded by the use of other data sources, for example, area, atmosphere, and the age of the plant.

17.6 Conclusion

Plant ailments have consistently been a huge worry in agriculture since they cause a decrease in crop quality and subsequently, production. Historically, it has been a very difficult task to detect plant diseases but with the recent emergence of new technologies and concepts like machine learning and deep learning, the task of plant diseases detection has become fairly easy.

A lot of researchers have utilized different deep learning architectures and transfer learning approaches for disease detection, and have achieved high accuracies. But these approaches also have some limitations and restrictions. The main restriction is lack of data quantity and quality. Also, it is difficult to detect multiple simultaneous disorders when images are analyzed as a whole and some disorders produce symptoms that look the same visually. Recent developments in this field are showing promise to solving these limitations and the future is definitely bright.

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Punam Bedi, Pushkar Gole, and Sumit Kumar Agarwal

18 Using deep learning for image-based plant disease detection

Abstract: Food is one of the basic needs of human life. The demand for food is increasing due to an exponential increase in the world's population. To overcome such a massive demand for food, agricultural practitioners suggested the use of different insecticides and pesticides to increase the yield of the crops. The use of these insecticides and pesticides increases the yield of plants, but using these in large amounts can degrade the quality of the soil, which makes crops more prone to different diseases. These diseases can negatively affect the crop yield and reduce the profit of the farmers. If the farmers can sense the plant diseases in the initial stages, it is possible to take necessary actions to remedy the situation. However, detecting diseases in a large field of crops with naked eyes is a challenging task. Thus, to simplify this process, there is a need for a system for automatic detection of plant diseases. This system can be build using various artificial intelligence (AI) techniques. Deep learning is a class of algorithms in AI which is widely used in numerous domains nowadays. This chapter describes a solution to the problem of plant disease detection using deep learning techniques. This chapter includes an explanation about convolutional neural networks (CNNs), their fundamental building blocks, and the details of different modern CNN architectures such as LeNet-5 and AlexNet. A complete implementation of an automated disease detection system for peach plant using LeNet-5 architecture is also described. At the end of this chapter, an experimental analysis based on the train and the test accuracies of disease detection systems using different modern CNN architectures is presented. All these implementations use data from a very famous dataset named PlantVillage.

Keywords: deep learning in agriculture, plant disease detection, convolutional neural network

18.1 Introduction

The agricultural sector plays an important role in the economy of India. In India, the farming sector share is 16% in GDP and 10% in total export [1]. It is one of the most prominent occupations of the rural population. About three-fourth population

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https://doi.org/10.1515/9783110691276-018

of India is dependent on agriculture either directly or indirectly. Naturally, it is desired that the crops produced should be free of diseases and high quality.

A major problem associated with agriculture is that plants are susceptible to various diseases in their growing phase. This, in turn, causes different challenging issues like low crop yield and less profit. Our goal is to provide a solution to this problem. Manual detection of diseases in crops is very challenging and time-consuming. Hence, we discuss an automated system that detects plant diseases with the help of plants' leaf images. Many artificial intelligence (AI) techniques have been suggested by various researchers to detect plant diseases automatically. Machine learning and deep learning are two prominent AI techniques used for this work.

Machine learning is an AI technique that learns hidden patterns in data so that it can be used for prediction. There are different machine learning techniques such as decision tree classifier, k-nearest neighbor classifier, and Naive Bayes classifier. All machine learning techniques suffer from two prominent issues. First, they are unable to automatically extract image classification features such as shape, texture, and color. Second, they require a significant amount of time to process large datasets of higher dimensions.

Deep learning is a subset of machine learning techniques which is motivated by architecture of neurons found in human cerebrum. It uses artificial neural networks (ANNs) and its other variants like recurrent neural networks (RNNs) and convolutional neural networks (CNNs) to discover the hidden patterns in the data for prediction [2]. Unlike machine learning, deep learning techniques automatically extract various features from raw data, and hence removing the need for a separate feature extraction module. The amount of time required to process large datasets of higher dimensions can also be significantly decreased in deep learning. In Section 18.2, we discuss the several research works that have been carried out in the literature to detect plant diseases automatically using machine learning and deep learning techniques.

As already discussed, deep learning offers significant advantages over the traditional machine learning approach. Hence, our main focus in this chapter is on deep learning. In Section 18.3, we discuss different architectures used in deep learning. CNN (CNN) is one such architecture.

CNN offers significant advantages over other variants of ANNs. It uses a convolution operation (discussed in Section 18.4.1) which extracts various spatial features from given images. These features play an important role in enhancing the performance of image classification. Hence, CNN is the deep learning technique that we have used to solve our problem. Section 18.4 talks about CNN and its building blocks in more depth. The process of detecting diseases in plants using CNN consists of five steps: data gathering, data augmentation, data preprocessing, classification, and performance evaluation. We explore these steps in Section 18.5.

A CNN architecture comprises several convolution layers, pooling layers, and fully connected layers. There are different modern CNN architectures like LeNet-5, and AlexNet, VGGNet-16 which differ from each other in terms of the number of convolution layers, pooling layers, activation functions, and so on. In Section 18.6, we discuss five modern CNN architectures: LeNet-5 [3], AlexNet [4], VGGNet-16 [5], GoogLeNet [6], and residual network (ResNet) [7].

LeNet-5 is a simple and easily understandable model. We describe the complete implementation of an automated plant disease detection system using LeNet-5 architecture in Section 18.7 of this chapter. The model is trained for detecting diseases in peach crops using images from a famous dataset named PlantVillage. We have used Python for implementing the LeNet-5 model. However, it can also be implemented in other programming languages like C++ and Java.

We have also implemented automatic plant disease detection systems for peach plant using other modern CNN architectures described in Section 18.6. In Section 18.8, we present a comparative analysis of these systems with the help of different graphs. The comparison among them is based on different performance evaluation metrics: training accuracy and testing accuracy.

18.2 Plant disease detection – state of the art

Many researchers have been working on plant disease detection with the help of leaf images using machine learning or deep learning methods. This section reviews different state-of-the-art systems based on machine learning or deep learning techniques available in literature.

18.2.1 Machine learning-based approaches

Naik et al. used support vector machine (SVM) for plant disease detection [8]. They considered four diseases: black rout, fungal, powdery mildew, and scorch. They used SVM to detect whether a leaf was infected or not and used a neural network to identify the class of disease if it was infected. The leaf images were captured using cameras and scanners. Preprocessing steps were performed on the captured images. These included filtering and image segmentation. Various texture and color related features were extracted from the preprocessed images using the genetic algorithm. The extracted features were fed into the neural network as input for classification. The accuracy of the SVM and the neural network was found to be 87.77% and 95.74%, respectively.

Ahmed et al. developed a disease detection system for rice plant using machine learning techniques [9]. They identified three different diseases in rice plants: brown spot, bacterial blight, and leaf smut. They used logistic regression, naive Bayes classifier, k-nearest neighbor, and decision tree classifier for classification of the diseases on a dataset fetched from UCI repository. They found that the decision tree classifier outperformed other classification algorithms with an accuracy of 97.91%.

Panigrahi et al. applied various machine learning techniques for detecting diseases in maize [10]. They used various supervised machine learning techniques such as SVM, k-nearest neighbor classifier, decision tree classifier, random forest classifier, and naïve Bayes classifier. These classifiers were applied to maize leaf images that were extracted from the PlantVillage dataset. To improve the accuracy of classification, image segmentation was also performed on the leaf images. Random forest classifier outperformed other classification algorithms with an accuracy of 79.23%.

Mahapatra et al. developed a plant disease detection system for various leaves present in the PlantVillage dataset [11]. They extracted different color, texture, and shape features from images. Other than these features, they also considered a plant's name as its feature. Different classification algorithms like logistic regression, decision tree classifier, k-nearest neighbor classifier, linear discriminant analysis, Gaussian naïve Bayes classifier, and SVM classifier were used for classification. In their experiment, the SVM outperformed others with an accuracy of 91%.

Rao et al. developed a system that used SVMs and k-nearest neighbor classifiers to identify diseases in rice plants [12]. They considered four diseases in rice plants: bacterial blight of rice, rice blast, rice tungro, and false smut. They achieved the best accuracy of 89.74% using SVMs. They also made this system available on the cloud so that farmers could quickly know whether their crops were diseased or not by uploading images of the crop.

18.2.2 Deep learning based approaches

Mohanty et al. used different modern CNN architectures for plant disease detection using leaf images [13]. They used two popular CNN architectures named AlexNet and GoogLeNet on the PlantVillage dataset. This dataset contains 54,306 images of healthy and diseased plant leaf images, which are distributed among 38 different classes. They performed 60 experiments by varying different parameters like CNN architecture (AlexNet, GoogLeNet), training mechanism (transfer learning or training from scratch), type of images (color, grayscale, and segmented), and train–test set distribution. Out of these 60 experimental configurations, transfer learning in GoogLeNet architecture using colored image version of the dataset partitioned in an 80–20% split of train and test set outperformed others with an accuracy of 99.34%.

Kumar and Vani performed different experiments on disease detection in tomato leaves using CNNs [14]. They used various CNN architectures like LeNet-5, VGGNet, ResNet, and Xception on tomato leaf images extracted from the PlantVillage dataset. There are 14,903 images of tomato leaves, which are evenly distributed among 10 classes. Out of the different CNN architectures, VGGNet-16 outperformed others with an accuracy of 99.25%.

Lin et al. proposed a model for powdery mildew disease in cucumber plants [15]. They used CNN for classification and deep learning for image segmentation. They proposed a semantic segmentation model based on CNN for the segmentation of powdery mildew disease pixels from the leaf images. The average accuracy of image segmentation was found to be 96.08%. Their model outperformed the existing segmentation schemes: k-means, random forest, and gradient boosting decision tree.

Zhong and Zhao proposed three novel methods of regression, focus loss function, and multilabel classification based on DenseNet-121 for disease identification in apple plants [16]. They gathered apple leaf images from a publicly available dataset named AI-Challenger-Plant Disease Recognition.[1] The accuracies of the proposed methods were 93.51%, 93.71%, and 93.31%, respectively, on the test data. This outperformed the conventional multiclass classification where cross-entropy loss was used.

Chen et al. designed a system to identify diseases in rice and maize plants with the help of VGGNet CNN architecture [17]. Instead of training the model from scratch, they used a pretrained VGGNet model trained on a dataset named ImageNet. It contained images of different categories in a large amount. Their model achieved 97.57% train accuracy and 91.83% test accuracy.

Different research works that use machine learning approaches perform feature extraction manually; however, in deep learning approaches, feature extraction is not done manually because deep learning techniques extract various important features automatically. In the next section, we explore various deep learning techniques that help in understanding our automated system for disease detection in plants.

18.3 Deep learning

Deep learning is based on learning using deep neural networks (DNNs) or its other variants such as CNN and RNN. The word “deep” in deep learning connotes the number of layers in a neural network and its other variants. As discussed earlier, deep learning has two prominent advantages over machine learning techniques. First, there is no need for a separate feature extraction module. Second, it decreases the amount of time to process large datasets of higher dimensions with the help of different application programming interfaces (APIs) like Keras, PyTorch, and Tensorflow. These APIs use graphics processing units to accelerate the training process of the deep learning model. In this section, we have discussed three different architectures of deep learning: DNN, RNN, and CNN.

1 Available at https://challenger.ai/.

18.3.1 Deep neural network

It is a classical, fully connected neural network in which neurons of adjacent layers are interconnected to each other. Each layer of the network has several neurons and an activation function that introduces nonlinearity in network, which is very useful for extracting different complex hidden features present in the input data. The initial layer and last layer of the network are termed as input layer and output layer, respectively. The intermediate layers between the input layer and the output layer are known as hidden layers. Figure 18.1 represents a typical six-layer DNN.

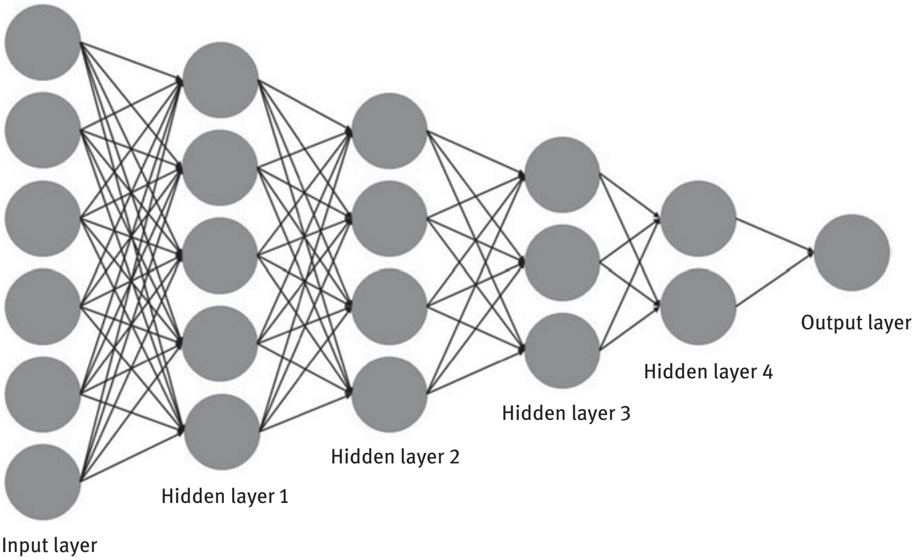

Figure 18.1: A typical six-layer multilayer perceptron.

18.3.2 Recurrent Neural Network

It is a type of neural network which takes output present at time $t-1$ as an input to compute output at time t. RNN deals with sequential data and it is used in speech recognition, time-series forecasting, and so on. A typical RNN architecture is shown in Figure 18.2.

18.3.3 Convolutional neural network

It is also a variant of neural network which is inspired by the human visual system. A neural network which uses convolution operation instead of simple multiplication of

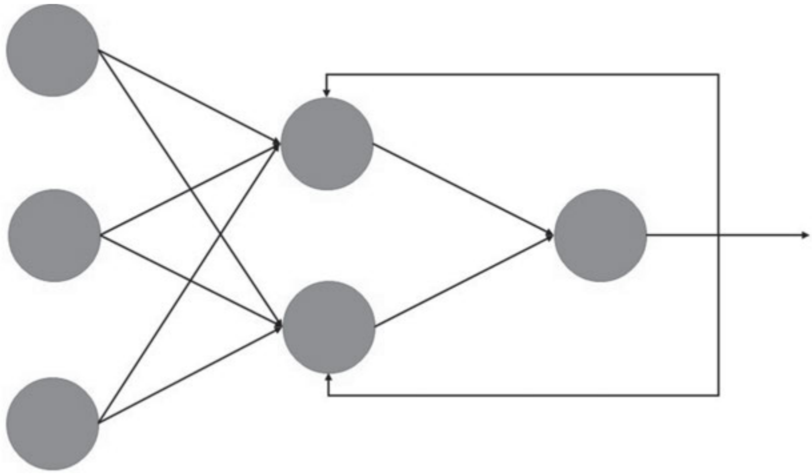

Figure 18.2: A typical RNN architecture.

matrices in at least one of its layers is known as a CNN [18]. CNN offers significant advantages when dealing with images and time-series data [19]. A typical block diagram of CNN architecture is shown in Figure 18.3.

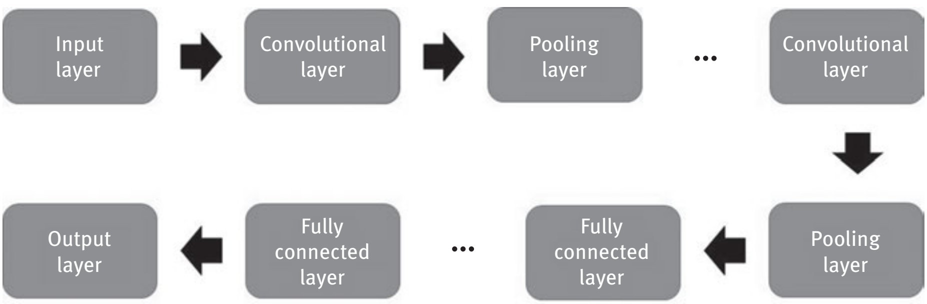

Figure 18.3: A typical block diagram of CNN architecture.

CNN is used in various computer vision applications like image classification, object detection, and object segmentation. This is because CNN can extract various spatial features from the given images using the convolution operation. These features play an essential role in improving the performance in image classification and other computer vision applications. Thus, for our problem of detecting diseases in leaf images, we use CNN. Hence, in the next section, we explore the various building blocks of CNN in detail.

18.4 Building blocks of CNN

There are three fundamental building blocks of CNN: convolution, pooling, and activation functions. These building blocks are explained in the following sections.

18.4.1 Convolution

The convolution operation is defined on two real-valued functions: f and g. It produces a third function that expresses the effect of function f on function g. The expression for convolution operation can be defined as follows:

$$h(t) = (f \star g)\ (t) = \int f(a) g(t-a) da \tag{18.1}$$

In terms of CNN, the first function, that is, f is termed as input, the second function, that is, g is termed as a kernel or a filter, and the output function h is known as the feature map. The above expression of convolution operation works in the continuous domain. In the discrete domain, we can assume that $f,\ g: I \to I$ and the expression for convolution operation can be expressed as follows:

$$h(t) = (f \star g)(t) = \sum_{a=-\infty}^{\infty} f(a) g(t-a) \tag{18.2}$$

In deep learning applications, the kernel and the input are multidimensional arrays. These multidimensional arrays are also known as tensors. Since each element of these multidimensional arrays of kernels and inputs is stored separately, we can assume that the values of these functions are nonzero for the finite set of points for which the values are stored. Hence, we can implement the infinite summation defined in the above equation as a finite summation over the elements of the multidimensional array.

Till now, we have defined convolution operation on one-dimensional data, but it can also be defined for higher dimensional data like images (two dimensions). Let us consider an input image stored in a two-dimensional array X of size $m \times n$ and a kernel stored in a two-dimensional array K of size $i \times j$. The expression for convolution operation defined on input X and kernel K is as follows:

$$S(i,\ j) = (X^{*}K)(i,\ j) = \sum_m \sum_n X(m,\ n) K(i-m,\ j-n) \tag{18.3}$$

Using commutative law, eq. (18.3) can be rewritten as follows:

$$S(i,\ j) = (K^{*}X)(i,\ j) = \sum_m \sum_n X(i-m,\ j-n) K(m,\ n) \tag{18.4}$$

The formula defined in eq. (18.4) can be used directly in many deep learning libraries. Some neural network libraries implement the convolution operation according to eq. (18.5). This operation is known as cross-correlation:

$$S(i,\ j) = (X^*K)(i,\ j) = \sum_m \sum_n X(i+m,\ j+n)K(m,\ n) \tag{18.5}$$

Figure 18.4 presents an example of convolution operation according to eq. (18.3) applied to a two-dimensional tensor. In this example, we have a two-dimensional array of size 5×4 as input and a kernel of size 3×3. The kernel moves on the input array by a fixed position in horizontal as well as in vertical direction (1 in this example). This fixed position is known as stride. The default value of stride is $(1,\ 1)$ in a two-dimensional convolution. If the value of the stride is greater than one, then the size of the feature map is reduced. This may lead to loss of data.

Let us reconsider the example of convolution presented in Figure 18.4. In this example, we have an input matrix of size 5×4 and a kernel matrix of size 3×3. After carrying out the convolution operation, the size of resultant matrix is 2×3. Using this example, we can see that every time a convolution operation is performed, the dimensionality of the output is decreased. In other words, the size of the input image gets smaller after every convolution operation and it vanishes after some convolutions. This places an upper bound on number of convolution operations that can be applied in a network, which in turn limits the depth of a CNN. Moreover, it can be observed that the elements on the corners and the edges of the input matrix are less utilized compared to the elements at the center. To address these two issues, we use padding.

Padding is the process of appending layers of zeroes to the borders of the input matrix. This increases the area of the input matrix on which the convolution operation has to be performed. This ensures that the dimensionality of the input image does not decrease after performing a convolution operation. Moreover, multiple layers of padding ensure that all elements of the input matrix are utilized well. Figure 18.5 depicts a padding on 4×4 input matrix. There are two types of paddings:

1. Valid padding: In this type of padding, no layer of zeroes is appended to the input matrix, and the output matrix contains the result of only valid convolution operations.
2. Same padding: In this type of padding, k layers of zeroes are appended to the input matrix such that the dimensionality of the resultant matrix remains the same as that of the input matrix after convolution operations are performed. Let us consider an input matrix of size $n\times n$ and a kernel of size $h\times h$, then the value of k can be calculated using eq. (18.6):

$$n + 2k - h + 1 = n \Rightarrow k = \frac{h-1}{2} \tag{10.6}$$

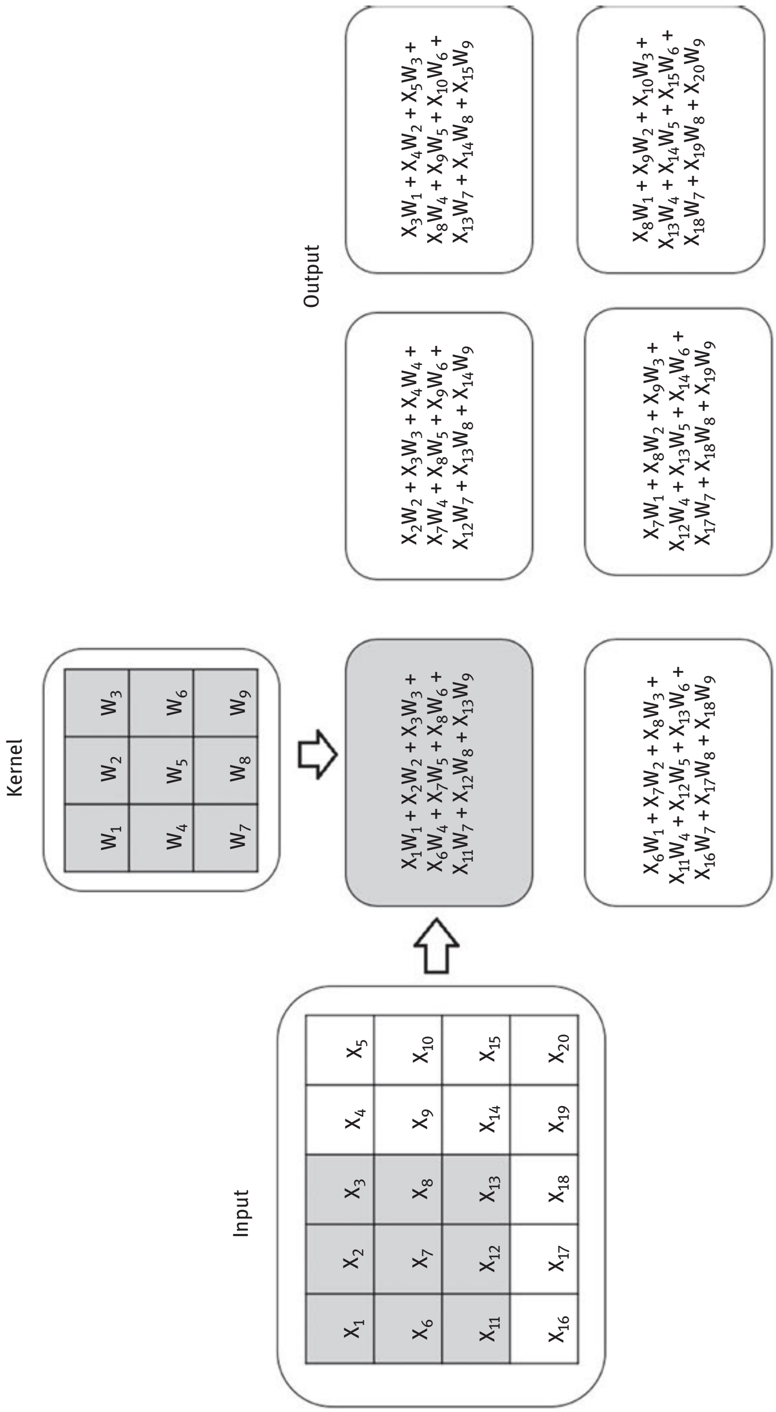

Figure 18.4: An example of a two-dimensional convolution operation.

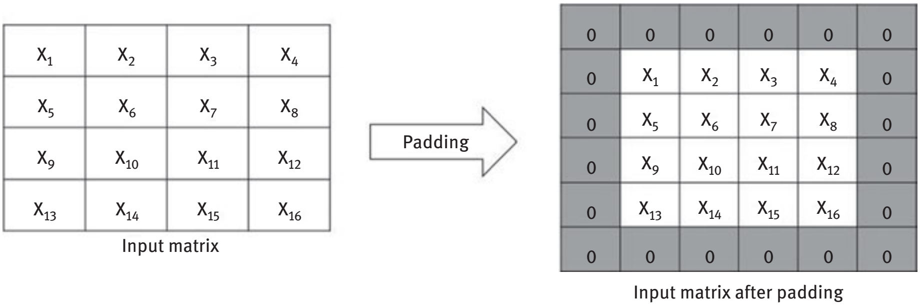

Figure 18.5: Padding operation on an input matrix of size 4×4 and kernel size of 3×3, so the value of k can be computed using eq. (18.6), that is, $k = \frac{3-1}{2} = 1$.

In CNN, the convolution operation is used to extract various spatial and temporal features from input images. The convolutional layer of CNN performs the convolution operation on input images to get different feature maps. These feature maps are further used in image classification. We can use multiple kernels/filters simultaneously on an input image. A typical CNN can have more than one convolutional layer. The first convolutional layer captures low-level features like edges, the orientation of gradient, and color. Layers that are placed at the end of a CNN extract high-level features, which help the network in understanding the input images.

18.4.2 Activation functions

The convolution operation is a linear mapping that is not sufficient to extract complex features present in different images. To extract these complex features, activation functions are used. Some of the most common activation functions that are used in CNN are described as follows:

1. Sigmoid function: It is also known as logistic activation function and is defined in eq. (18.7). The output of this function ranges from 0 to 1. Figure 18.6 shows the graph of the sigmoid function. There are two disadvantages of the sigmoid function. First, it slows the learning process of the model because of the vanishing gradient[2] problem. Second, this function can only be used in two-class problems:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{18.7}$$

2 While training the model using stochastic gradient descent algorithm, if gradient of error with respect to the weights of the model becomes almost zero or vanishes, then the weights of the model are not changed further and the learning process eventually stops. This problem is termed as vanishing gradient problem.

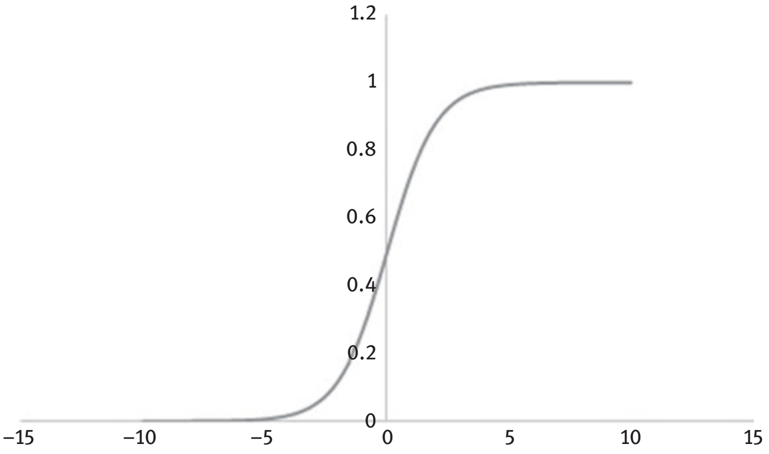

Figure 18.6: Sigmoid function.

2. Tangent hyperbolic (tanh) function: It is also a type of logistic activation function. The expression for this function is defined in eq. (18.8). The range of this function is from −1 to 1. Figure 18.7 shows the graph of the tanh function

$$f(x) = \tanh x \tag{18.8}$$

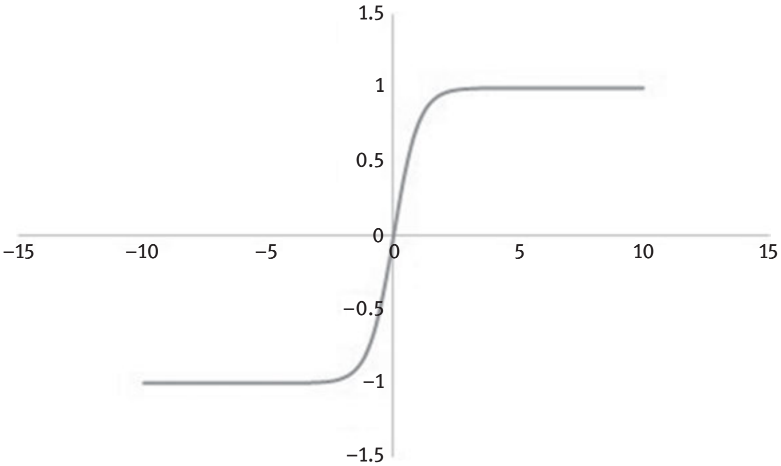

Figure 18.7: tanh function.

3. Rectified linear unit (ReLu) function: It is computationally efficient as compared to tanh and sigmoid functions. Its mathematical expression is defined in eq. (18.9). It is widely used in hidden layers of CNNs. Figure 18.8 represents the ReLu function graphically. The output of this function ranges from 0 to ∞:

$$f(x) = \max(0, x) \tag{18.9}$$

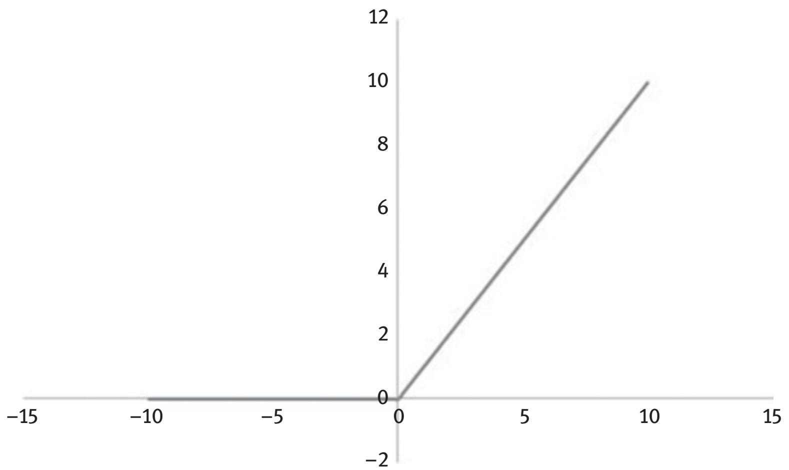

Figure 18.8: ReLu function.

4. Softmax function: It is a more generalized form of the sigmoid function. It can be used in multiclass problems. Its mathematic expression is defined in eq. (18.10), where *k* is the number of classes. The value of this function also ranges from 0 to 1:

$$f(x_i) = \frac{e^{x_i}}{\sum_{j=0}^{k} e^{x_j}} \tag{18.10}$$

18.4.3 Pooling

Pooling is used to reduce the dimensionality of the input images which in turn reduces the number of training parameters. It is performed on each feature map independently. It selects only one output from its neighborhood using some statistics. Some of these statistics are max pooling [20], average pooling, weighted average, and L^2 norm. Max pooling selects the maximum output from its neighborhood. This has been represented in Figure 18.9. Other methods include average pooling which

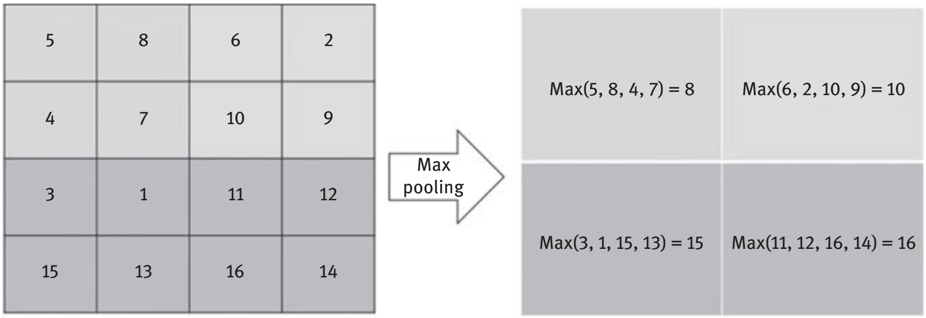

Figure 18.9: Max pooling operation in 2×2 neighborhood with stride 2.

selects the average of its neighbors, L^2 norm which calculates the Euclidean norm in its neighborhood, and weighted average which takes a weighted average of its neighbors using a pixel's distance from the central pixel as weight.

In this section, we discussed different building blocks of CNN. In the next section, we have illustrated five steps needed to build an automated system for plant disease detection using CNN.

18.5 Using CNN for plant disease detection

In the previous section, we explored different building blocks of CNN. In this section, we describe five steps to implement an automatic plant disease detection model using CNN. These steps are data gathering, data augmentation, data preprocessing, classification, and performance evaluation. We have explained the implementation of each step using the Python programming language. However, it can be implemented in other programming languages as well, like C++ and Java. These steps are common to all CNN architectures described in Section 18.6.

18.5.1 Data gathering

Data gathering is the first step to build any CNN model. For building a CNN model for automatic plant disease detection, this step comprises gathering both diseased and healthy leaves of a plant by capturing it from the field using a digital camera. There are some publicly available datasets, shown in Table 18.1, which can also be used to build a CNN model for automatic plant disease detection.

Table 18.1: Details of different publicly available datasets for plant disease detection.

S. no.	Dataset name	Dataset description	URL
1	PlantVillage [21]	It contains 54,303 leaf images of different plants which are evenly distributed in 38 classes.	https://www.tensorflow.org/datasets/catalog/plant_village
2	Rice leaf diseases [22]	It contains 120 leaf images of rice plant which are equally distributed in 3 different classes.	https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases
3	One-hundred plant species leaves [23]	It contains 1,600 leaf images of different plants which are equally distributed in 16 different classes.	https://archive.ics.uci.edu/ml/datasets/One-hundred+plant+species+leaves+data+set
4	Plant Doc [24]	It contains 2,598 leaf images of 13 plant species, which are evenly distributed in 17 different classes.	https://github.com/pratikkayal/PlantDoc-Dataset
5	AI-Challenger-Plant Disease Recognition [16]	It contains the leaf images of 10 different plants.	https://challenger.ai/

18.5.2 Data augmentation

Data augmentation is a technique that artificially enlarges the dataset of images with the help of different image processing techniques such as image rotation, zoom in, zoom out and image flipping. If the size of the leaf image dataset is small, then there is a chance that the model learns the training data too well as compared to the testing data. This problem is known as overfitting. It can also be used to solve the overfitting problem.

In Python, there is a library named Augmentor,[3] which can be used for data augmentation [25]. It uses different image processing techniques (image rotation, zoom in, zoom out, image flipping, etc.) for data augmentation. Figure 18.10 shows

```
import Augmentor
p = Augmentor.DataPipeline('/leaf_images)
p.rotate(probability=0.7,max_left_rotation=20,max_right_rotation=20)
p.zoom(probability=0.2,min_factor=1.0,max_factor=1.4)
p.flip_left_right(probability=0.4)
p.sample(10)
```

Figure 18.10: Code snippet for augmentation.

3 Available at https://pypi.org/project/Augmentor/

a code snippet used to create 10 leaf images from a single leaf image using Augmentor library. Figure 18.11 shows an original leaf image and its corresponding augmented leaf images.

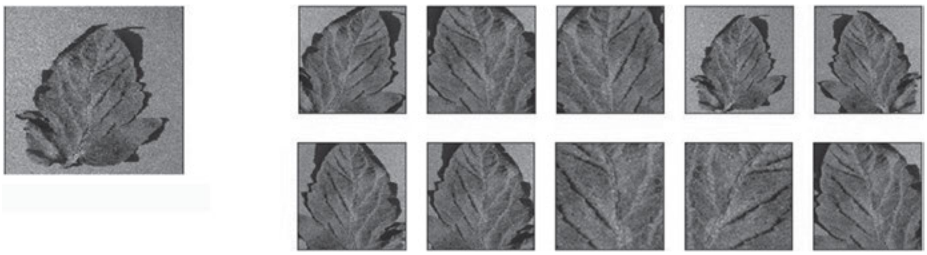

Figure 18.11: (a) An original leaf image and (b) augmented leaf images.

18.5.3 Data preprocessing

Data preprocessing is a technique that is used to transform raw data into a usable format. There are different preprocessing techniques such as image resizing and image segmentation that can be used before feeding the images into the model. These techniques have been described as follows:

1. Image resizing: It is a technique by which one can either decrease or increase the resolution of the original image. Most popular methods of image resizing use interpolation of original image pixels. There are different interpolation techniques like bilinear interpolation, nearest neighbor interpolation, and bicubic interpolation [26]. While training the CNN model for automatic plant disease detection, images of the leaves have to be resized to a lower resolution so that the training process becomes faster. It can be done with the help of different Python libraries like OpenCV, Matplotlib, Pillow, and others. Figure 18.12 shows a code snippet to resize the image using OpenCV. Figure 18.13 shows an original leaf image and its corresponding resized image.

```
import cv2
leaf_img = cv2.cv2.imread('leaf.jpg')
resized_leaf_image = cv2.cv2.resize(leaf_img,dsize=(128,128))
print('Original Leaf Image Size:',leaf_img.shape)
print('Resized Leaf Image Size:',resized_leaf_image.shape)
```

Figure 18.12: Code snippet to resize image using OpenCV library.

(a) (b)

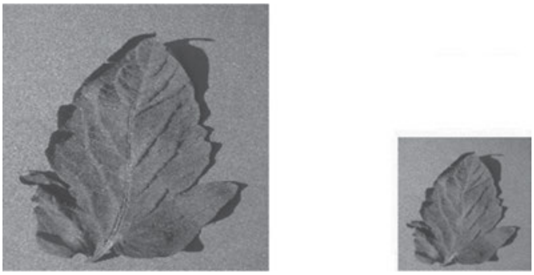

Figure 18.13: (a) Original leaf image of size 256×256 and (b) resized leaf image of size 128×128.

2. Image segmentation: It is used to divide images into their constituting object or regions. Most segmentation algorithms exploit two basic properties of the image intensity values: similarity and discontinuity. There are various methods to facilitate image segmentation like region splitting, region growing, region merging, and thresholding [27]. Deep learning techniques like SegNet [28], U-Net [29], R-CNN [30] and Faster R-CNN [31] are also used for image segmentation because these techniques can achieve higher accuracy as compared to traditional image processing methods. Image segmentation becomes a necessary data preprocessing technique when the leaf images are captured directly from the field because it contains other objects like the ground and the stem of the plant. Segmentation also enhances the performance of the model. Figure 18.14 shows an original leaf image and its corresponding segmented leaf image.

(a) (b)

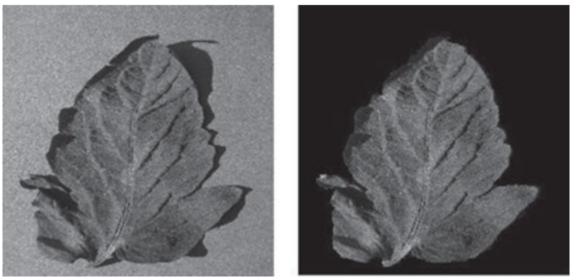

Figure 18.14: (a) Original leaf image and (b) segmented leaf image.

18.5.4 Classification

After preprocessing, we start with the classification of images. Image classification is the process of classifying an image as per its visual content. The process of classification is divided into two phases: model creation and model training. These phases are described in detail as follows:

1. Model creation: We can create a CNN model by stacking multiple convolution layers (with varying filter size and number of filters), pooling layers, and fully connected layers. This model can be created by using the *Model* API of Keras library in Python. A summary of different layers of the model can be seen by using *model.summary()* method.
2. Model training: After creating a model, we compile this model by using some predefined optimizer (Adam, RMSProp, AdaDelta, etc.) and some predefined loss function (binary crossentropy, categorical crossentropy, etc.). We can also define our own optimizer and loss function. In Python, the model can be compiled by using the *model.compile()* function of *Model* API. After this, the model can be trained on the preprocessed dataset of leaf images. The model can be trained by using the *model.fit()* function.

18.5.5 Performance evaluation

Once a model is trained, we calculate the performance of model with the help of training and testing data to get the training performance of the model and the testing performance of the model, respectively. There are two ways of getting testing data. First, dividing the entire dataset into training data and testing data in some ratio (say 80:20). Second, getting a new dataset, similar to the training dataset, as the testing dataset. To evaluate a model's performance, we predict the class label of the different images exist in training data and the testing data with the help of trained model. We then compare them with the actual class labels of the images present in training dataset and testing dataset to get the training and testing performance of trained model, respectively. There are different evaluation metrics, such as training accuracy, testing accuracy, training loss, and testing loss, which can be used to calculate the performance of trained model.

18.6 Modern CNN architectures

A CNN architecture is defined as a set of convolution layers, pooling layers, and fully connected layers, stacked together. There are different modern CNN architectures such as LeNet-5, AlexNet, and VGGNet-16 which differ from each other with respect to the number of pooling layers, number of convolution layers, activation functions, and so on. In this section, we discuss five famous modern CNN architectures in detail: LeNet-5, AlexNet, VGGNet-16, GoogLeNet, and ResNet.

18.6.1 LeNet-5

Lecun et al. designed a five-layer CNN architecture for handwritten character recognition, which is also known as LeNet-5 [3]. It is designed to recognize handwritten characters present on a bank check automatically. It consists of two convolution layers of size 5×5 with stride one, two average-pooling layers of size 2×2, and three fully connected layers in which the last layer is the output layer. The first convolution layer has 6 kernels and the second convolution layer has 16 kernels. The convolution layers and the fully connected layers have tanh activation, except for the last fully connected layer, that have softmax activation. The input size of an image for LeNet-5 is 32×32. If the input image is not of size 32×32, then it should be resized to 32×32. LeNet-5 architecture is shown diagrammatically in Figure 18.15. Table 18.2 shows the details of this CNN architecture. This architecture can achieve a high test accuracy and a low error rate of 99.05% and 0.95%, respectively.

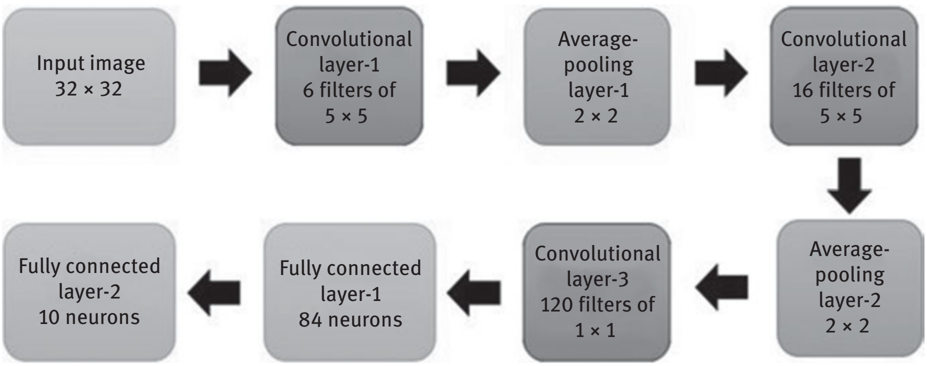

Figure 18.15: Diagrammatic view of LeNet-5 architecture.

18.6.2 AlexNet

Krizhevsky et al. developed a CNN architecture named AlexNet [4], which was able to successfully classify 1.2 million images from ImageNet[4] dataset, in the large-scale visual recognition challenge (LSRVC) organized in year 2012. AlexNet won the ILSRVC-2012 with top-5[5] error rate as 17.0% on the test data. It takes images of size

4 ImageNet dataset contains 15 million labeled images from 22,000 classes. There are 1.2 million training images, 50,000 validation images, and 150,000 testing images.

5 Top-5 error rate is defined as the number of images in the test set for which its ground truth is not in the five most probable labels predicted by the model divided by the total number of test images.

Table 18.2: Layerwise details of LeNet-5 architecture.

Layer	Size	Size of filter	Number of feature maps	Stride	Activation function
Input	32×32	–	1	–	–
Convolution #1	$28 \times 28 \times 6$	5×5	6	1	tanh
Average pooling #1	$14 \times 14 \times 3$	2×2	6	2	–
Convolution #2	$10 \times 10 \times 16$	5×5	16	1	tanh
Average pooling #2	$5 \times 5 \times 16$	2×2	16	2	–
Convolution #3	$1 \times 1 \times 120$	5×5	120	1	tanh
Fully connected #1	84	–	–	–	tanh
Fully connected #2	10	–	–	–	softmax

224×224 as input, and if the input images are not of this size, then one should resize them. It is a very deep CNN architecture as compared with other architectures like LeNet-5. It contains 60 million trainable parameters and 650,000 neurons with five convolution layers, three max-pooling layers, and three fully connected layers. All the convolution and fully connected layers have a ReLu activation function except for the last fully connected layer that has softmax activation. The AlexNet architecture is shown in Figure 18.16.

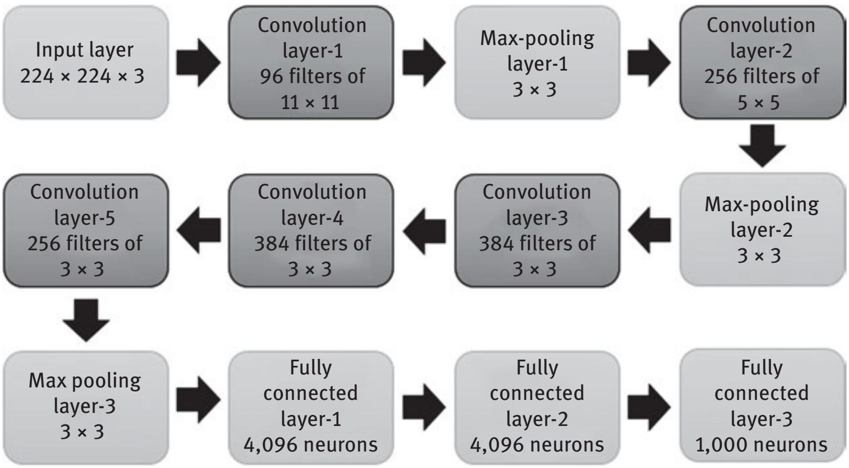

Figure 18.16: Diagrammatic view of AlexNet CNN architecture.

18.6.3 VGGNet-16

Simonyan et al. from the Visual Geometry Group of Oxford University designed a CNN architecture named VGGNet-16 [5]. It consists of 16 trainable parameter layers with 138 million trainable parameters. It was the first runner-up of ILSRVC-2014 with a top-5 error rate of around 7%. The size of input images to this architecture is $224\times224\times3$. It has 13 convolution layers of size 3×3 each, with stride 1 and same padding. It also has three fully connected layers in which the first two layers have 4,096 neurons each and the last one, which acts as output layer, has 1,000 neurons. All the convolution and fully connected layers have ReLu activation except for the last fully connected layer in which softmax activation function is used. The VGGNet-16 architecture is shown in Figure 18.17.

18.6.4 GoogLeNet

Szegedy et al. from Google, developed a CNN model named GoogLeNet in 2014 [6]. It was the winner of ILSVRC-2014. They used a new Inception module (shown in Figure 18.18) in a layer-by-layer fashion, to design the architecture of GoogLeNet.

The Inception module uses convolution of three different size filters (1×1, 3×3, and 5×5) and max-pooling operation simultaneously to enhance the feature extraction process of CNN. Each convolution and max-pooling operation is performed with stride 1 and same padding. This ensures that the dimensionality of output remains the same as the dimensionality of the input. Figure 18.18 shows an inefficient version of the Inception module since it takes more operations as compared to its efficient version shown in Figure 18.19.

GoogLeNet contains 22 layers having trainable parameters and five layers without trainable parameters. The image input size to this CNN architecture is $224\times224\times3$. It contains 6.797 million trainable parameters and achieves a 6.67% top-5 error rate.

18.6.5 ResNet

Kaming et al. showed that the performance of a network may decrease as the depth of the network increases [7]. The vanishing gradient problem may be one of the reasons behind the degradation of performance in the network. Due to this, we could not increase the depth of network beyond a certain limit and it placed an upper bound on the depth of the network. To overcome this shortcoming, they designed a CNN architecture known as ResNet. ResNet consists of a novel module named residual block (shown in Figure 18.21).

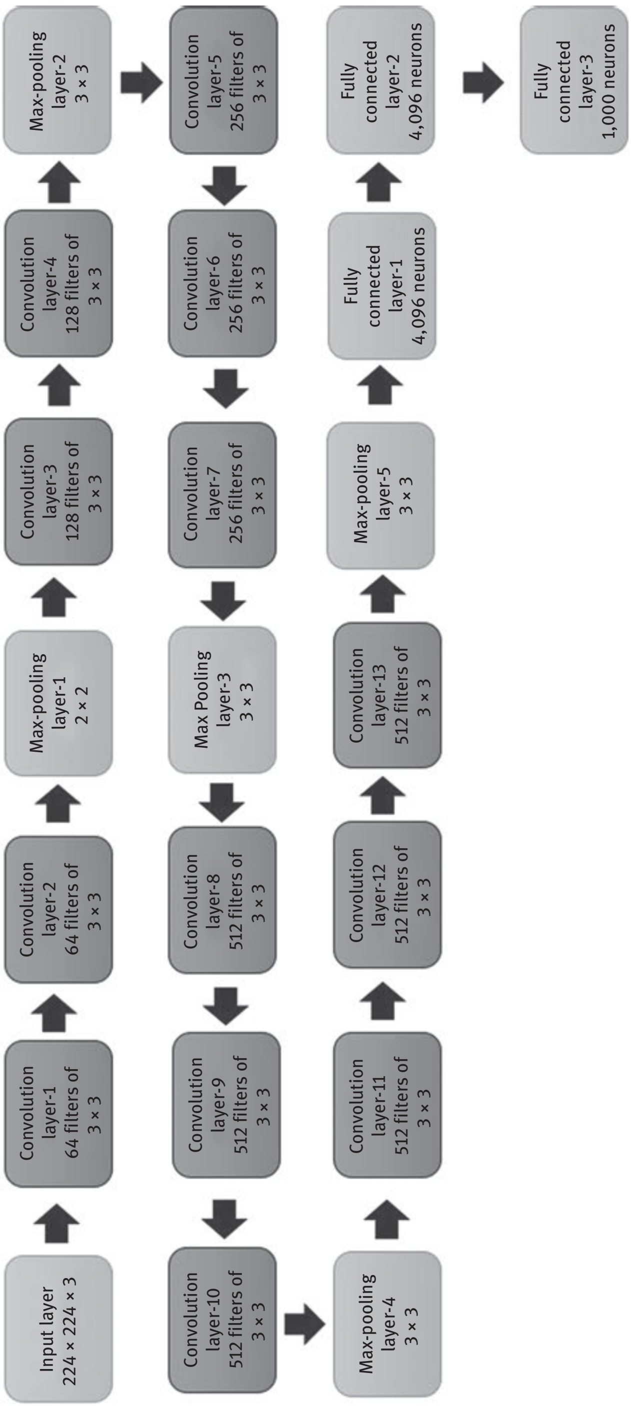

Figure 18.17: Diagrammatic view of VGGNet-16 CNN architecture.

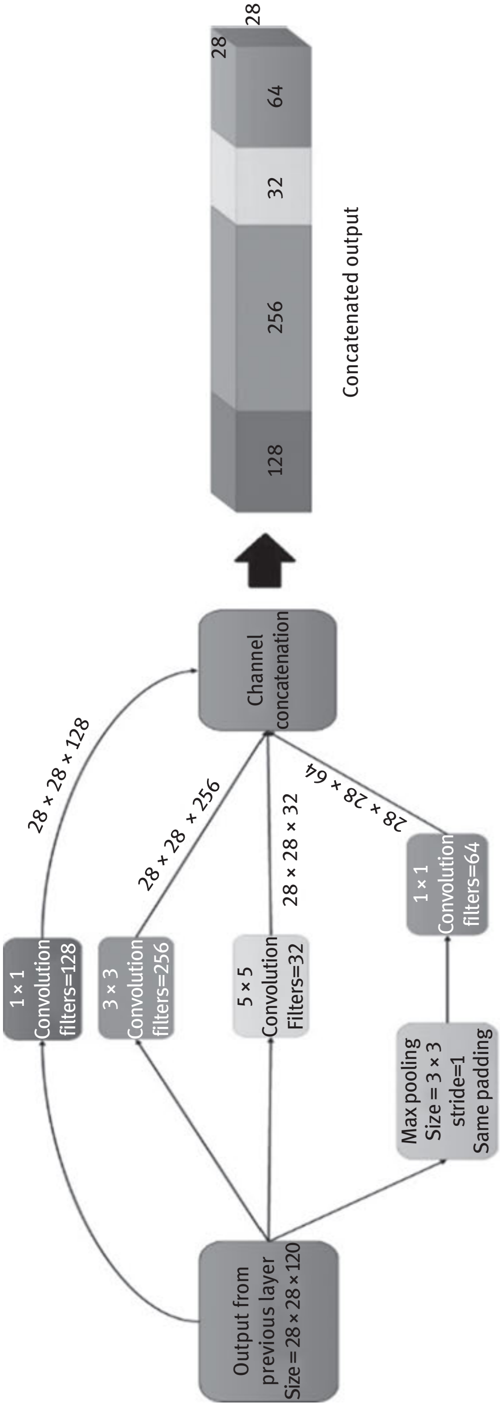

Figure 18.18: Diagrammatic view of Inception module (inefficient version).

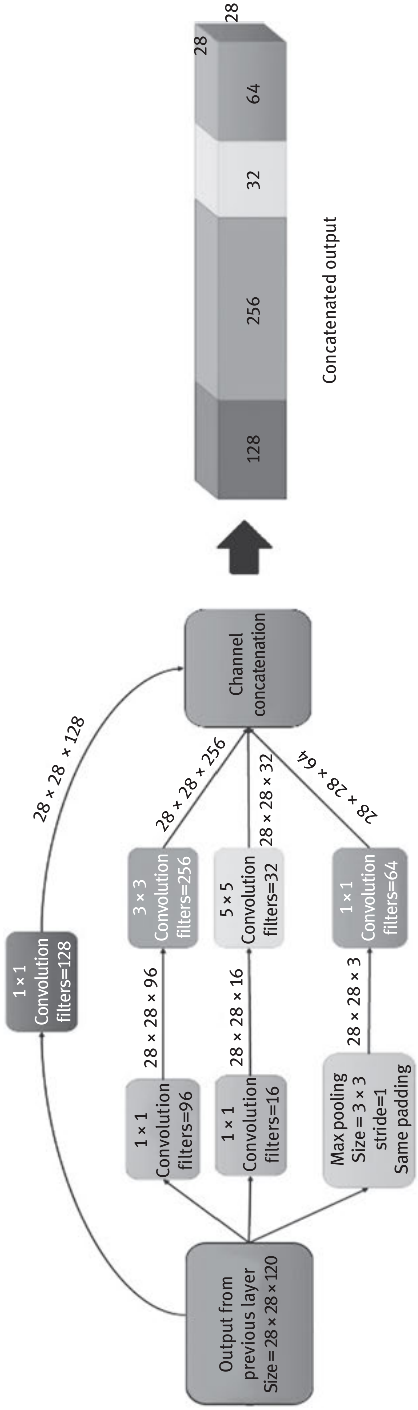

Figure 18.19: Diagrammatic view of Inception module (efficient version).

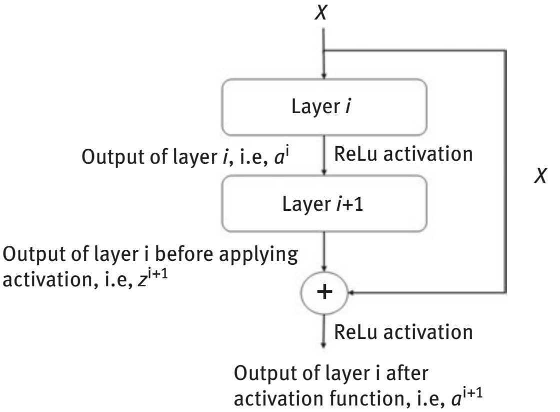

Figure 18.20: Diagrammatic view of residual block with two layers.

```
import tensorflow_dataset as tfds
import numpy as np
plant_data = tfds.load("plant_village")
images = []
labels = []
import numpy as np
for instance in tfds.as_numpy(plant_data['train']):
  if instance['label'] == 16 or instance['label'] == 17:
    images.append(instance['image'])
    labels.append(instance['label'])
images = np.array(images)
labels = np.array(labels)
```

Figure 18.21: Code snippet to load the images of leaves of peach from the PlantVillage dataset that is embedded in the Tensorflow library.

Let us consider a two-layer residual block, as shown in Figure 18.20. If the input to ith layer is X then $a^i = \text{ReLu}(W^i \cdot X)$, $z^{i+1} = W^{i+1} \cdot a^i$, and $a^{i+1} = \text{ReLu}\left(z^{i+1} + X\right)$, where W^i and W^{i+1} are the weights for ith and $i+1$th layers, respectively. We can see that the information flows not only through a straight path, but also flows from the skip connection. Thus, the effective depth of the network decreases without removing the intermediate layers. Hence, we can increase the depth of the network by using different residual blocks in a stacked fashion to achieve a high accuracy.

Kaming et al. presented a 152-layer deep residual network in their paper that outperformed other previous state-of-the-art systems [7]. They won the ILSRVC-2015 with a very low top-5 error rate of 3.57% on the ImageNet dataset.

In this section, we explored five famous modern CNN architectures. Among these architectures, LeNet-5 is comparatively easier to understand, is simpler to implement, and is computationally cheaper. In the next section, we describe the implementation of an automatic plant disease detection system using LeNet-5 architecture. We skip the implementation details for creating the automated system using the other four architectures but discuss their experimental results in Section 18.8.

18.7 Implementing LeNet-5 model in Python for plant disease detection using PlantVillage dataset

In this section, we discuss the implementation of an automated system for detecting diseases in peach plants using the LeNet-5 architecture discussed in Section 18.6.1. The model is trained on peach plants' leaf images taken from the PlantVillage dataset. We have implemented the LeNet-5 model in Python with the help of Keras library. As already discussed, it can be implemented in other programming languages as well.

18.7.1 Dataset description

We use the images of peach crops' leaves present in the PlantVillage dataset [21] embedded in the Tensorflow library to train our CNN model. The dataset also contains images of leaves of other plants like tomato and potato. To extract only the images of peach from the dataset, we impose a selection criterion on the label of leaf images. The label for peach is either 16 or 17. There are 2,657 images of peach leaves in the dataset. They are distributed into two classes. Each image is of size $256 \times 256 \times 3$. Here, 3 stands for an RGB image. Figure 18.21 shows a code snippet to load the images of the leaves of peach plants from the PlantVillage dataset using the Tensorflow library. Figure 18.22 shows some images of peach leaves from the PlantVillage dataset.

18.7.2 Data preprocessing

The class labels of leaf images are integers. Before feeding these class labels to our CNN model for training, they are converted to a categorical form. As there are two classes, we replace labels 16 and 17 by 0 and 1, respectively. A code snippet to convert class labels to categorical form is shown in Figure 18.23.

Since the size of the input image for LeNet is 32×32, we resize the leaf images to 32×32. This is done with the help of the OpenCV library of Python. A code snippet to resize the leaf images is shown in Figure 18.24. After resizing, the size of resized_images array becomes $2,657 \times 32 \times 32 \times 3$ since there are 2,657 leaf images in the dataset.

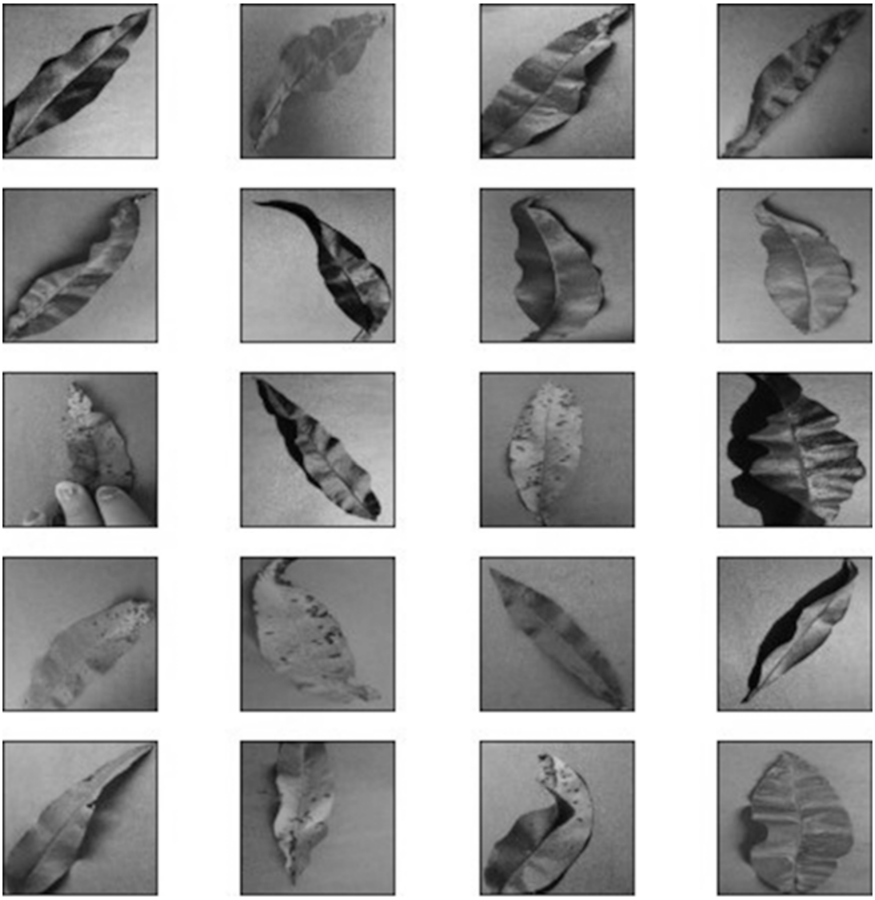

Figure 18.22: Leaf images of peach plant taken from the PlantVillage dataset.

```
labels = np.where(labels==16,0,1)
np.unique(labels)
```

Figure 18.23: Code snippet to convert class labels to categorical form.

```
import cv2
import numpy as np
resized_images = []
for image in images:
   resized_images.append(cv2.cv2.resize(image,dsize=(32,32)))
resized_images = np.array(resized_image)
```

Figure 18.24: Code snippet to resize the leaf images.

18.7.3 Creating LeNet-5 model

After data preprocessing, we are ready to create the LeNet-5 model (described in Section 18.5.1). To create the LeNet-5 model, we import different layers like *Conv2D* (for convolution operation), *AveragePooling2D* (for average pooling), *Dense* (fully connected layer), *Input* (to take input), and *Dropout* (to avoid overfitting) from keras.layers. Figure 18.25 shows a code to create the LeNet-5 model.

```
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense,Conv2D, AveragePooling2D,Flatten
input_layer = Input(shape=(32,32,3))
convolution_layer_1 = Conv2D(filters=6,kernel_size=(5,5),activation='tanh',strides=(1,1))(input_layer)
average_pooling_layer_1 = AveragePooling2D(pool_size=(2,2))(convolution_layer_1)
convolution_layer_2 = Conv2D(filters=16,kernel_size=(5,5),activation='tanh',strides=(1,1))(average_pooling_layer_1)
average_pooling_layer_2 = AveragePooling2D(pool_size=(2,2))(convolution_layer_2)
convolution_layer_3 = Conv2D(filters=120,kernel_size=(1,1),activation='tanh',strides=(1,1))(average_pooling_layer_2)
flatten_layer = Flatten()(convolution_layer_3)
fully_connected_layer_1 = Dense(units=84,activation='tanh')
output_layer = Dense(1,activation='sigmoid')(fully_connected_layer_1)
model = Model(input_layer,output_layer,name='LeNet_5')
model.compile(loss='binary_crossentropy',metrics=['accuracy'])
model.summary()
```

Figure 18.25: Code snippet to create LeNet-5 model.

After creating the LeNet-5 model, we compile it with *Adam* optimizer, *categorical crossentropy* loss, and *accuracy* metrics. Now, we train the LeNet-5 model on the PlantVillage dataset with batch size of 64 and 10 epochs. The PlantVillage dataset is divided into training and testing set in a 70:30 ratio. Figure 18.26 shows a code snippet to compile and train the model.

```
model.compile(optimizer='adam',loss="categorical_crossentropy",metrics=["accuracy"])
history=model.fit(resized_images,labels,batch_size=64,epochs=10,validation_split=0.3,shuffle=True)
```

Figure 18.26: Code snippet to compile and train the LeNet-5 model.

18.7.4 Analyzing the performance of the trained model

After training the model for 10 epochs, we can plot the training accuracy, testing accuracy, train loss, and test loss with respect to epochs (shown in Figure 18.28) using the Matplotlib library. Figure 18.27 shows a code snippet to plot train accuracy, test accuracy, and train loss, test loss with respect to epochs. We have achieved a training accuracy of 95.53% and testing accuracy of 92.78% in our LeNet-5 model.

In this section, we described the complete implementation for creating an automated system for detecting diseases in peach crops using the LeNet-5 model. In the next section, we explore other CNN architectures with the help of an experimental analysis based on their train and test accuracies in detecting diseases in peach plants.

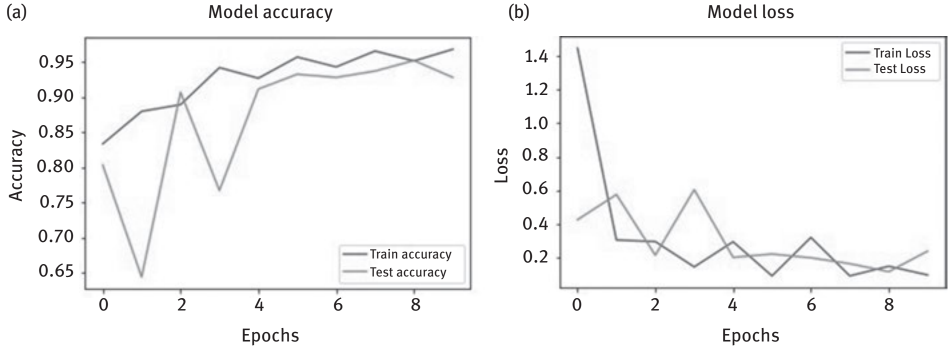

Figure 18.27: (a) Code snippet to plot train and test loss and (b) code snippet to plot train and test accuracy.

```
import matplotlib.pyplot as plt
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend(['Train Loss','Test Loss'], loc='best')
plt.show()
```

(a)

```
import matplotlib.pyplot as plt
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend(['Train Accuracy','Test Accuracy'], loc='best')
plt.show()
```

(b)

Figure 18.28: (a) Plot of train and test loss and (b) plot of train and test accuracy.

18.8 Experimental analysis

In the previous section, we explored the complete implementation of a LeNet-5 model. To explore other CNN architectures, we have implemented an automated disease detection system for peach plant using every CNN architecture discussed in Section 18.6 and have presented a comparative analysis based on their train and test accuracies. We have not discussed the implementation details of these models as they are similar to the LeNet-5 model described in the previous section.

Table 18.3 shows the consolidated results obtained from different CNN architecture in terms of train and test accuracies. We have found that the AlexNet outperforms other CNN architectures with a training accuracy of 99.45% and testing accuracy of 98.50%.

Table 18.3: Accuracies of different CNN architectures.

CNN architecture	Train accuracy (%)	Test accuracy (%)
LeNet-5	95.53	92.78
AlexNet	99.45	98.50
VGGNet-16	93.83	93.68
GoogLeNet	98.02	97.24
ResNet-50	99.35	96.69

The performance of different modern CNN architectures is shown in Figure 18.29.

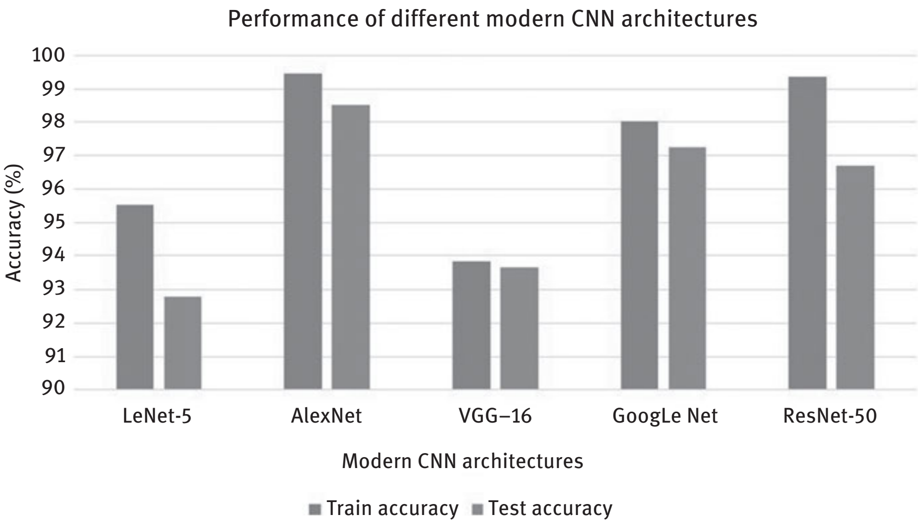

Figure 18.29: Performance of different modern CNN architectures.

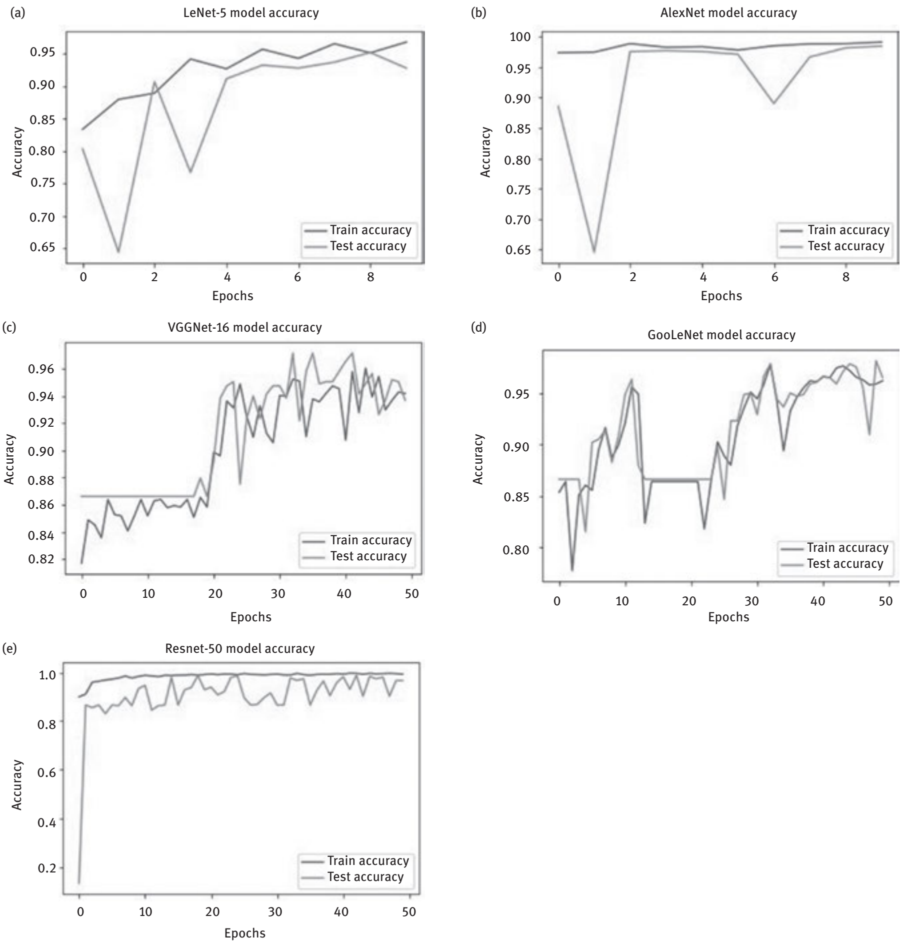

Figure 18.30: Variation of test and train accuracies with respect to epochs for different modern CNN architectures on the leaf images of peach crop extracted from PlantVillage dataset, (a) LeNet-5, (b) AlexNet, (c) VGGNet-16, (d) GoogLeNet, and (e) ResNet-50.

Figure 18.30 represents the variation of test and train accuracies with respect to epochs. To avoid overfitting (discussed in Section 18.5.2), we have used the concept of early stopping[6] in our implementation.

6 It is a technique used to solve the overfitting problem in a model. In this technique, the training process of the model stops when its performance stops to improve over several epochs.

18.9 Conclusion

In this chapter, we presented a solution to the problem of plant disease detection by the aid of plants' leaf images using deep learning techniques. We discussed various state-of-the-art techniques that exist in the literature to solve this problem. We saw why deep learning is preferred over machine learning for our specific problem. We also explored different deep learning architectures and concluded that CNN was the most effective among them for dealing with image data. After this, we understood different building blocks of CNN. This helped in establishing a foundation for understanding and implementing an automated plant disease detection system.

Following this, we presented the five steps used for designing a CNN model for processing leaf images for disease detection. After this, we discussed the concept of a CNN architecture and explored five famous modern CNN architectures: LeNet-5, AlexNet, VGGNet-16, GoogLeNet, and ResNet. We presented the complete implementation of an automatic system for detecting diseases in peach plants using LeNet-5 architecture. At the end of this chapter, we further explored the five CNN architectures with the help of experimental analysis. We implemented five different disease detection systems for peach plants and compared them on their train and test accuracies. Out of the five systems, the system using AlexNet outperformed the others with 99.45% train accuracy and 98.50% test accuracy.

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https://doi.org/10.1515/9783110691276-019

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