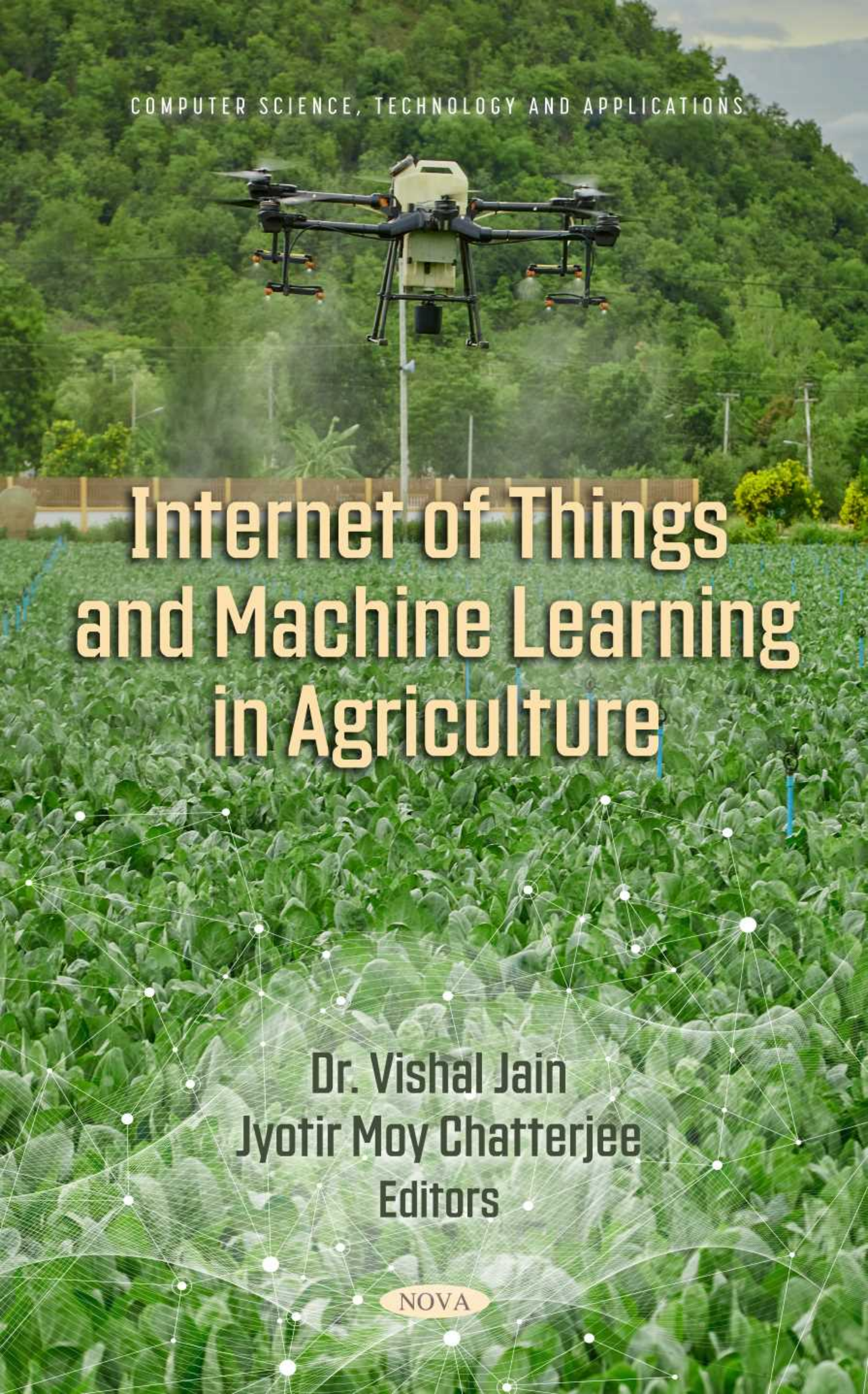

COMPUTER SCIENCE, TECHNOLOGY AND APPLICATIONS

Internet of Things and Machine Learning in Agriculture

Dr. Vishal Jain
Jyotir Moy Chatterjee
Editors

NOVA

COMPUTER SCIENCE, TECHNOLOGY AND APPLICATIONS

INTERNET OF THINGS AND MACHINE LEARNING IN AGRICULTURE

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VISHAL JAIN

AND

JYOTIR MOY CHATTERJEE

EDITORS

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CONTENTS

PREFACE

Agriculture is one of the most fundamental human activities. As long as we've pursued it, we've tried to master it. Better techniques meant greater yields. This, in turn, kept humans happier and healthier – and helped birth modern society as we know it. There's only one hitch in this success story, however. As our farming has expanded, the 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 70% by 2050 to keep up with global demand. With global populations rising, 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 (ML) and the Internet of Things (IoT) can play a very promising role in the Agricultural Industry. Some examples will be: an artificial intelligence programmed drone to monitor the field, an IoT designed automated crop watering system, sensors embedded in the field to monitor temperature and humidity, etc. The agriculture industry is the largest in the world, but when it comes to innovation here 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 applying analytics and getting the insight that aid decisions around harvesting. In this book, we will try to explore the impacts of ML and IoT in the agriculture sector and we will try to point out the challenges facing the agro-industry which can be solved by both Machine Learning and the Internet of Things.

Chapter 1 brings together the components required in smart farming and how they are enabled by artificial intelligence and IoT. Chapter 2 begins with the history of agriculture, followed by advances in agricultural technology, highlighting IoT, smart farming using IoT, the various uses of IoT in agriculture, benefits and restrictions. Chapter 3 proposes an IoT-based model to alert farmers for soil moisture conditions, potential damage in agricultural land from the fire and automatic water irrigation started at low moisture of soil or fire. Chapters 4 and 5 outline intelligent systems, the studies aimed to develop intelligent systems for identification of pests and diseases and current literature with proposed solutions in the form of information technology through Internet of Things (IoT), image analysis, machine learning, AI algorithms, and cloud services. Chapter 6 demonstrates the potential of agricultural wireless sensors and the Internet of Things (IoT), as well as the challenges that are expected to arise when this technology is integrated with traditional farming techniques. Chapter 7 proposes a methodology which helps in early detection of disease or infection in agricultural crops by suggesting a sampling methodology to detect the infection at an early stage. Chapter 8 aims at developing an automated smart irrigation system with the help of the Internet of Things. Its aim is to maintain an adequate amount of water needed by the crop by monitoring the amount of soil moisture, temperature and humidity in the soil. Chapter 9 discusses the core ICT-enabled facilities and instruments that have a potential productive effect on farmers, rural citizens and the entire nation's agricultural economy. Chapter 10 discusses adapting the capability of IoT for data collection of features of crops and for automated decision making with data analytics algorithms.

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Chapter 1

SMART FARMING ENABLING TECHNOLOGIES: A SYSTEMATIC REVIEW

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ABSTRACT

Providing food security to the global population is a challenge and is included as an objective in Sustainable Development Goals of the United Nations, 2030. There is a need to increase the production and quality of crops to ensure food security. Farming is moving from being labour-intensive to technology-intensive to increase the yield. Smart farming is the application of technology in farming. This paper includes a review of Artificial Intelligence and IoT, working and applications. Artificial Intelligence is making the machine do things that at present humans do better. It has three refined branches- Machine learning (ML), Artificial Neural Networks (NN) and Deep Learning (DL). Machine Learning is making the machine learn from existing data using mathematical modelling. Neural Network is a collection of neurons that simulates the human brain. Deep Learning is the inclusion of hundreds

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of layers in the neural network. Internet of things (IoT) is an enabling technology that connects electronic devices with the internet. These devices can then be controlled and monitored remotely. This paper discusses the architecture of IoT applications. IoT involves sensors for data collection through cloud computing and the use of this data for decision-making using artificial intelligence methods. This chapter brings together the components of smart farming and how artificial intelligence and IoT enable these. These components are soil management, conditions for sowing, enhancing soil fertility, rainfall prediction, irrigation system and water management, pesticide control, weed management, crop diseases, harvesting, storage management and transportation of crops.This chapter acts as a ready reference to the researchers in smart farming.

Keywords: smart farming, IoT, cloud, applications of technology

INTRODUCTION

Providing food security to the global population is a challenge. Sustainable Development Goals of the United Nations, 2030 includes Food Security as an objective.An increase in production and enhancing the quality of crops will ensure food security. Farming is moving from being labour-intensive to technology-intensive to increase the yield and quality. Smart farming is the term coined for the application of technology in farming.

In the coming years, people and places are going to be surrounded by sensors. These sensors collect some vital data from the environment and relay it to the cloud platforms. Analysis of this data helps in decision-making using methods based on Artificial Intelligence.Combining IoT with Artificial Intelligence and several independent machine learning applications are promising for innovating farming.Smart farming aims to optimize costs, time and resources. It helps in improving the quality and variety of products.

The organization of the paper is as follows. Section 2 includes the review of Artificial intelligence techniques, namely, machine learning, neural networks and deep learning along with the applications of each.

Section 3 discusses IoT technology and its applications. Section 4 discusses the components of smart farming. Section 5 includes the applications of artificial intelligence and IoT to agriculture giving way to smart farming. Section 6 includes conclusions.

REVIEW OF ARTIFICIAL INTELLIGENCE

The world is changing due to the impact of Artificial Intelligence. Artificial Intelligence is making the machine do things that at present humans do better. The famous Alan Turing test proposed- when the user cannot differentiate whether the response is coming from human or computer, that is the ultimate goal of Artificial Intelligence. The tools of Artificial Intelligence- Machine Learning, Neural Network and Deep Learning are killer methods that are changing the research output favourably. These tools accept the input-output sets and help in predicting the outcome for new input cases. Machine Learning is making the machine learn from existing data. The learning can be supervised or unsupervised. In supervised learning, the machine has sample input-output combinations to learn the pattern in training data. In unsupervised learning, the machine clusters data on its own without any training data. Machine learning is based on mathematical equations where the new data is estimated on basis of training data. The weights for new data are calculated through the application of mathematical rules. Neural Network is a simulation of the human brain where software consists of neurons. Each neuron can save certain information and propagates to the next layer of neurons depending on activation function and threshold value (just like synapses in the human brain). A neural network can be a single layer of neurons to multiple layer neurons. Deep Learning is an extension of the neural network further where the number of layers in NN architecture is high. Such networks can identify the features from the data and get trained to predict the outcome.

Machine learning (Bishop, 2006) is based on existing data. Data can be of two types- where we have a group of X inputs with Y output. Here, the task is to estimate the weights (w) which when applied to new data can predict the Y accurately. This is supervised learning as shown in Figure 1. Supervised learning outcomes can be categorical or continuous. In categorical outcomes, the output is a discrete value. In continuous outcome, the output is a real value. Supervised learning where we know the features of what is being predicted. In the second type of machine learning, we do not know the Y output. We generate a grouping among data points based on X input and clusters of common points are formed. Then the points that occur in the neighbouring area are predicted to be similar. The data is not divided into training and test data. All the data is given in one go. In supervised learning, the data is divided into training and test data.

Machine learning algorithms have a base in mathematics. General machine learning methods discussed in (Bishop, 2006) and (Ethem Alpaydın, 2010) are Bayesian Decision Theory, Parametric Methods: Multivariate Methods, Dimensionality Reduction, Clustering; Nonparametric Methods: Decision Trees, Linear Discrimination; Bayesian Estimation, Hidden Markov Models and Graphical Models. Some other common names include Linear Regression, K-nearest neighbour, Principal Component Analysis and SVM.

The methods mentioned above are some basic models and ever since there has been a lot of development in these methods. Several branches of machine learning algorithms are defined for each application.

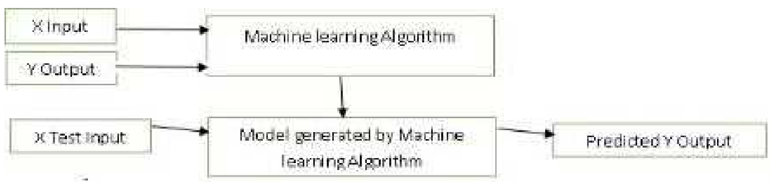

Figure 1. Supervised Learning in Machine learning.

Some applications of Machine learning methods are discussed below. Web Search Engine: Boyan, etal. (Boyan, Freitag and Joachims, 1996) discusses the application of information retrieval techniques to fetching web pages in a web server. The paper discusses the use of Reinforcement

Learning to improve the search engine output. Yoganarasimhan (Yoganarasimhan, 2019) uses machine learning for the customization of search results based on search history. Jiang (Jiang et. al., 2018) discusses the use of geospatial information and machine learning to optimize search. Image Processing and Computer Vision: One field that has progressed tremendously is image processing. There are many branches of image processing and computer vision that are being investigated by the research community. Handwriting Recognition is being performed by several techniques including SVM, KNN, HMM, random forest and tree classifier with a high accuracy rate of 90-95% (Firdaus and Vaidehi, 2020). Face Recognition is performed using SVM (Guo, Li, and Chan, 2001), Bayes method (Moghaddam, Jebara and Pentland, 2000), Xtreme learning (Zong and Huang, 2011) and PCA (KwangIn, Keechul and Hang, 2002). Object Recognition is another area of research. It is performed using several techniques including SVM for 3D Object recognition (Massimiliano and Alessandro, 1998) and unsupervised learning (Le, 2013). Dougherty (Dougherty, 2011) discusses several Medical Image Processing problems and methods. Data Mining, Natural Language Processing, Education and Game Playing are other applications of machine learning.

The application of machine learning techniques to any problem requires three steps: (1) preparation of data (2) feature extraction and preparation of input for machine learning algorithm (3) choose and apply the machine learning method. The collection and preparation of data is an extensive task. The more comprehensive is the nature of input data, the accurate are the results. Feature Extraction is an area of research in itself. Traditionally, the machine learning techniques had to be implemented in a programming language but now packages like Matlab, R and python offer ready to use packages.

Neural Networks is a branch of Machine Learning. The model of Neural Networks is similar to the human brain. The Neurons hold information. Dendrites receive the stimuli information. If stimuli are strong, the neuron will transmit an electric signal to the next neuron through axioms and synapses. This interconnected neuron architecture of the human brain is simulated in Artificial neural networks (ANN). In ANN, the neurons have activation function and transfer functions. These functions have a mathematical basis. The input is applied to the neural entity by using the activation function. It makes use of weights and input multiplied together. These weights are calculated by the neural network during the training process. The learning in neural networks is shown in Figure 2.

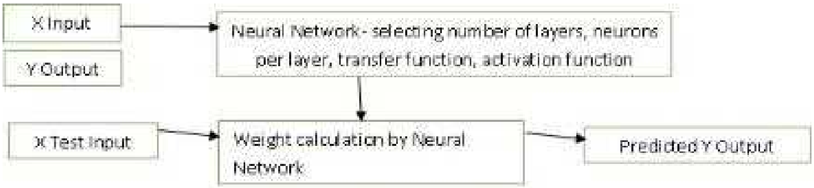

Figure 2. Learning in Neural Networks.

It is important to understand the difference between neural networks and other machine learning algorithms. The neural networks have a basis in human brain functioning and predict the output, Y for a given input, X. The calculation is performed using weights that are calculated during the training. The other machine learning algorithms apply a formula to X input values and predict the Y. The calculation, formula and working principle are different for the neural network and other machine learning algorithms.

The steps to use the neural networks are the same: collecting data, feature extraction and application of model by selecting the number of layers and neurons in each layer. There are several ready to use platforms example MatLab which have graphical tools to design a neural network.

Neural networks are of different types: Single layer perceptron, Multilayer perceptron, Feedforward Neural Network, Recurrent Neural Network.

Deep Learning is an extension of ANN where the number of layers is large in the network. Due to the increased number of layers, Deep learning can identify the patterns that ANN or ML could not capture. There are several types of Deep learning models: Convolutional neural network, Recursive neural network.

Deep Learning is an advancement of Neural Networks with hundreds of hidden layers. The increase in the number of layers leads to more realistic values in predicted values.There is a need for large datasets to train a deep learning system. It is capable of identifying the features on its own. Deep learning is a machine learning technique that makes computers learn by example. The performance of Deep Learning is far improved as compared to traditional methods.

The neural networks originally consisted of 2-3 hidden layers. But deep Learning systems have hundreds of hidden layers which make them highly accurate. It requires huge data such as the data generated by Big Data and on that data, it can find out relations among data without the human having to perform feature extraction.For example, the application is face recognition. The data required are 2D images of the faces and videos of faces. Deep learning networks are given the pixel values of the data images to identify the faces. Though Deep Learning is a subset of Machine Learning, some features of deep learning make it outperform machine learning in some applications. The features are summarized below in Table 1.

Some of the applications of Deep Learning are listed below in Table 2. Natural language processing involves the use of technology for understanding natural language and communicating in natural language. Several applications include virtual assistants that interact with the user and provide information, translations (convert between different natural languages), chatbots (communicate with user replacing human to answer customer services) and text generation (text correction and word suggestions in auto checking). Computer vision is another area where deep learning is used for remote surveillance. Several technologies used for this are drones, self-driving cars, remote sensing and aerospace. All these fields benefit from the machines enabled with vision using cameras. The service bots are computers replacing human customer care in not only answering queries but in the execution of tasks such as in banking the service bot can open and close accounts for users as the steps are fixed.

Similarly, online shopping, entertainment and customer experience with autosuggestions based on past customer selections and facilitation of placing orders. Face recognition, object recognition and image feature extraction can be performed with great accuracy using deep learning. Deep learning is applied for drug design and disease identification using medical imaging.

Table 1. Comparison of deep learning and machine learning

Criteria	**MachineLearning**	**DeepLearning**
FeatureExtraction	Manual	Performed by Network
Volumeofdata	The large volume of data may not improve the accuracy	Improves accuracy
TypeofFunction	Applies a single function or algorithm	Can apply multiple mathematical functions at different layers.
Hardware	Normal processor	High power processors

Table 2. Applications of deep learning

Natural Language Processing	Virtual assistants (Alexa) (Kepuska and Bohouta, 2018), Translations (Singh et. al., 2017), Chatbots (Wu and Yan, 2019), text generation (Marcheggiani and Perez-Beltrachini, 2018)
Computer Vision	Drones (Kim, Ryu, Yonchorhor, and Shim, 2020), Self Driving car (Rao and Frtunikj, 2018), remote Satellite vision (Zhu, et. al., 2017), Aerospace and Defence (Kuchuk, Podorozhniak., Hlavcheva, and Yaloveha, 2020).
Service Bots	Banking (Addo, Guegan, and Hassani, 2018), online-shopping (Koehn, Lessmann, and Schaal, 2020), entertainment (Min, Ha, Rowe, Mott and Lester, 2014), the customer experience (Bolton, et. al, 2018).
Images	Face Recognition (Hu, 2015), Image colourization (Zhang, Isola, and Efros, 2016)
Medicine and Science	drug identification (Gawehn, Hiss and Schneider, 2016), diagnosis of diseases (De Fauw, 2018)(Ferentinos, 2018)

REVIEW OF IOT

Internet of things (IoT) (Luigii, Antonio, Giacomo, 2010; Ashton, 2009; Xia, Yang, Wang and Vinel, 2012) is enabling technology that connects the electronic devices with the internet and these devices can be operated and monitored remotely. It also involves the use of sensors for data collection through cloud computing and the use of this data for important decision making.The Internet of Things generates data from millions of devices. This data, when used with Machine learning algorithms can generate hidden patterns and models that help predict future behaviour and events. Machine learning uncovers hidden insights in IoT data for fast, automated decision making.

The steps for the amalgamation of IoT with Machine learning are: First, IoT sensors are added to the machinery that senses environmental parameters such as vibration, noise, heat, and temperature. This data is saved using the cloud for analysis. Second, the machine learning algorithms are applied to this data collected. Third, the Machine learning model splits the data into training and testing. This ML model builds a hypothesis from the training data and test data is used to verify the same. Once a model has been validated, the live streaming of IoT sensor data can be attached to the ML model for remote decision making. The architecture of IoT is given in Figure 3.

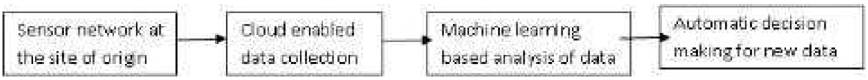

Figure 3. Architecture of IoT.

Applications of IoT summarized in (Zeinab, and Elmustafa, 2017) are:

1. A smart city (Jin, Gubbi, Marusic, and Palaniswami, 2014) is a city enabled by cloud and IoT technology where all the amenities and infrastructure components such as water, electricity,

transportation, energy, gas, telephone; are connected over the IoT network and remote decision making is available to make the life of citizens comfortable.

2. Smart Manufacturing (Kusiak, 2018) is the introduction of sensors in machines and the use of machine learning, cloud, data modelling and predictive analysis for better-performing products.
3. Smart Mobility (Faria, Brito, Baras, and Silva, 2017) includes Artificial Intelligence-based Transportation and Real-Time Traffic Management Systems where technology is used to decide the routes and manage congestion on roads.
4. Smart health (Ullah, Shah and Zhang, 2016) provide technology for providing patients' health data using smartphones and monitoring and taking corrective action remotely.
5. Smart grid and energy (Karnouskos, 2010) providing Internet of Energy and heterogeneous devices able to measure and share their energy consumption for energy management systems.
6. Smart home (Chong, Zhihao and Yifeng, 2011) by publishing the household wireless sensor network data to the web page of a remote server, users can control the household devices conveniently and remotely.

These are not exhaustive applications of IoT but these are the areas in which IoT applications are being deployed by the industry.

COMPONENTS OF SMART FARMING

Smart farming is the use of technology in farming. Along with biotechnology, biofertilizers and hybrid seeds, information and communication technology is deployed in farms for better management of the farming process. The areas where ICT can be applied in farming are shown in Figure 4 and discussed below:

1. Soil Management: Identifying the composition of soil and selection of proper crop variety according to the soil. Selection of those crops that will automatically leave the soil replenished and nourished. Avoiding overuse of fertilizers and use of bio-fertilizers.
2. Conditions for sowing: Identification of the right time to sow the crops. It involves the study of environmental factors such as weather, the water content of the soil, humidity, micronutrients in soil and so on, through sensors.
3. Enhancing soil fertility: this involves understanding the soil composition and micronutrients contents and enhancing it by deploying proper infrastructure to sprinkle appropriate fertilizers. This process should not make the soil acidic.
4. Rainfall prediction: Prediction of rainfall and completion of necessary farming activities before the timeline.
5. Irrigation system and water management: Keeping control of the soil moisture to create suitable conditions for germination and proper crop growth. Maintaining the right moisture in the soil all the time.
6. Pesticide control: Controlling the amounts of pesticides and avoiding pest infections. When and what quantity of pesticide to be sprinkled by an automatic dispenser.
7. Weed management: Preventing weed growth and monitoring the crops remotely and identifying a regular crop from a weed. Detection of the exact location in the field where the weeds are found.
8. Crop diseases: Early identification of crop diseases and preventing further spread in other plants.
9. Harvesting: help in timely and ICT enabled harvest.
10. Storage management:Store the crops inappropriate conditions, planning quantities to store and sell.
11. Transportation of crops: The sale of the crops in the markets at appropriate prices and transportation to the grain market using technology-enabled methods.

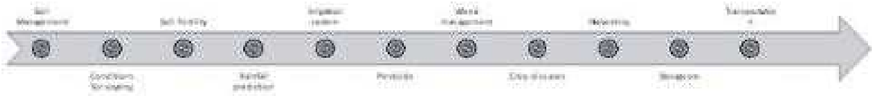

Figure 4. Components of smart farming.

APPLICATIONS OF ARTIFICIAL INTELLIGENCE AND IOT IN SMART FARMING

To support the above components of smart farming several technological resources are required (Navarro, Costa and Pereira, 2020). Such resources include devices for heat, precipitation, pressure, the chemical concentration of soil, drones, video cameras, MIS software, global positioning systems and communication networks. It involves computer vision for crop management using drones, extraction of weed pictures and crop disease pictures from the captures of drones, pest identification using 3D or 2D images. It also involves remote sensing for weather monitoring which is more specifically focused on a particular city or area. There is a need for sensors for measuring temperature, luminosity, humidity, pressure, ground chemical concentration and soil moisture level. The paper discusses the intelligent architecture for smart farming involving sensors for perception, networking for communication of information, data storage and processing using machine learning and applications that covers all the components of smart farming.

Jha, Doshi, Patel and Shah, 2019, have reviewed several Artificial Intelligence-based systems developed for maintenance of specific types of crops - Object-oriented expert system for Tea plantation,Tea Radial Basis Function networks, Rule-based expert system for general crops,Artificial neural Networks for Mango and Cassava; Hop plant Rule-based expert system. The paper also discusses a system for the botanical farm of a flower. It provides a system for leaf identification and watering using IoT.

While looking at the potential benefits of smart farming, the threats cannot be ignored. The greatest threat to smart farming is cybersecurity and protection (Gupta, Abdelsalam, Khorsandroo and Mittal, 2020).

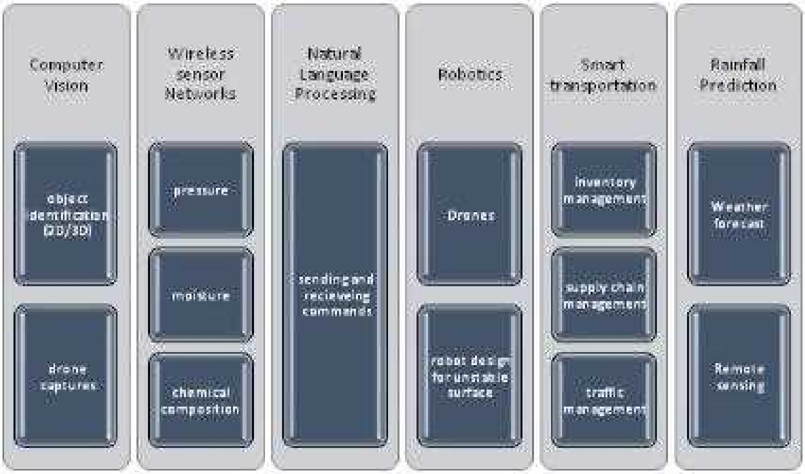

Figure 5. Applications of machine learning and IoT in Smart farming.

Figure 5 briefs the several ranges of machine learning and IoT applications and infrastructure required to implement smart farming.

CONCLUSION

As seen in the literature review, there are several applications of artificial intelligence and IoT that have become helpful in the implementation of smart farming. Smart farming is not a distant reality with a lot of research fraternity developing practical models and test data sets available for testing. The use of artificial intelligence and IoT in smart farming is indispensable and many applications of machine learning, deep learning and IoT can be used with smart farming. The key components of smart farming are soil management, irrigation system, weather prediction, pest control, fertilizer control, crop disease control, smart transportation, supply chain management and inventory management. There are several applications of machine learning and IoT that help in meeting these components of smart farming, as discussed in the paper. These technologies are still in the budding phase and extensive research is required to realize them.

Computer Vision is realized with development in object identification (2D/3D) and drone captures. Wireless sensor Networks are possible through a lot of physical and biosensors. Natural Language Processing is possible with the help of Machine learning and Deep learning. Robotics is realized with Drones and robot design for the unstable surface. Smart transportation is realized through inventory management, supply chain management and traffic management. Rainfall prediction is realized through Weather forecast and Remote sensing. All these are the applications of artificial intelligence. IoT sensor networks are used to collect the data and artificial intelligence techniques are used to process this data and take appropriate action.

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Chapter 2

INTERNET OF THINGS PLATFORM FOR SMART FARMING

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ABSTRACT

The growing demand for quality food and quantity has increased the need for agribusiness and stabilization. The Internet of Things (IoT) is the future which is influencing everyone's lives by acting intelligently. Research organizations and institutions of higher learning are constantly working to create solutions and products based on the IoT. The Internet of Things (IoT) is a technology that promises innovative solutions for modern agriculture. New Smart Farming innovations using IoT are slowly but firmly changing the nature of traditional farming methods, not only by making them more efficient but also by reducing farmers' costs. The goal is to spread technology that can send alerts to farmers via various platforms. Farmers will

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benefit from this product as it will provide them with real-time data from their farms (UV index, temperature, soil moisture, humidity, and so on), allowing them to take the necessary steps to increase crop yields while conserving resources (water, fertilizer).

The chapter begins with a history of agriculture, followed by advances in agricultural technology, smart farming using IoT. The chapter also highlights the benefits and the limitations of IoT in agriculture. This chapter also sheds light on the IoT's challenges, the scope of future agriculture, and emerging technologies.

Keywords: Internet of Thing (IoT), Livestock Monitoring, Stock Monitoring, Big Data, Precision Agriculture, Agriculture Drones, Artificial Intelligence (AI), Machine Learning (ML)

1. Agriculture

Human civilization began with the Stone Age, which was characterized by a nomadic lifestyle in which people moved from place to place and lived in transient settlements. The Neolithic period, also commonly known as the Neolithic Revolution, was the final phase of the Stone Age. This drastically altered people’s lifestyles, and people began farming rather than hunting.

The agricultural community emerged around 12,000 years ago when humans began to domesticate plants and animals. Crops cannot be cultivated or grown without the use of equipment, so Stone Age people had to invent a variety of farming tools to help them with their new horticultural lifestyle. Plows were created to break up roots and weeds in preparation for planting. By creating domesticity, families and larger groups were able to form communities and transition from a nomadic hunter-gatherer lifestyle reliant on foraging and hunting for survival [14, 22].

Agriculture is the science or practice of farming, which includes the cultivation of the soil for the development of yields as well as the raising of creatures to provide food, fleece, and other items. In a nutshell, horticulture includes soil preparation, planting, and animal raising [18].

2. AGRICULTURE PROCESS

Figure 1. Life Cycle of Agriculture and Source [15].

The life cycle of agriculture can be divided as follows:

- Soil preparation: This is the first stage of planting, as the soil is prepared by the farmers to plant the seeds. Wide clods of earth are cracked and the debris is removed, such as sticks, stones, and roots. Also, depending on the type of plant, use fertilizer and organic matter to create the ideal environment for the plants.
- Seed sowing: The stage necessitates consideration of the gap between two seeds as well as the depth at which seeds should be planted. Climate conditions such as temperature, humidity, and rainfall are critical at this time.
- Adding Fertilizers: Maintaining soil fertility is important for the farmer's ability to continue growing nutritious and safe crops. Fertilizers are used by farmers as potassium, phosphorus, and nitrogen are nutrients that the plant contains. Nutrients are actually fertilizers that are grown in the agricultural sector to

change the nutrients in the soil. This category also determines the quality of the crop.

- Irrigation: At this stage, the soil is required to be moist. The other factor that is maintained is humidity. Crop growth can be hampered by under watering or overwatering, which, if not done correctly, can result in crop damage.
- Weed control: Unwelcome plants that grow around crops or along farm boundaries are called weeds. Weed control is critical to consider because weeds reduce yields, raise production costs, obstruct reaping and reduce crop quality.
- Harvesting: In this step, crops are collected from the fields. This practice necessitates a large number of workers, making it a labour-intensive activity. Cleaning, arranging, packing, and cooling are all part of the post-harvest process.
- Storage: It is the third stage of the post-reap strategy. This is the point at which the products are kept in a manner that guarantees food security outside of agrarian seasons. Yield bundling and transportation are likewise included [15].

3. Challenges in Traditional Agriculture

- Climate factors like precipitation, temperature, and dampness all play a part in the agricultural lifecycle. Environmental change is a consequence of expanding deforestation and outflows, making it incomprehensible for ranchers to settle on choices for the most proficient methods of gathering, sowing seeds, and collecting.
- Any crop requires a specific kind of soil nourishment. In soil, three principal supplements are required: nitrogen (N), phosphorus (P), and potassium (K). Supplemental insufficiency can make crops of low quality.
- Weed control is basic in horticulture, as demonstrated by the farming lifecycle. If not managed, it might prompt an increment

in underway expenses, just as the retention of supplements from the dirt brings about supplement adequacy.

4. Technological Development in Agriculture

A. Innovation has assumed a significant part since the origin of the Industrial Revolution, which acquainted farming apparatus with automating rural work like furrows, seeders, growers, and reapers [8].

B. This essentially expanded ranchers' efficiency and was a significant defining moment for rural innovation. Many homestead occupations recently performed by difficult-working creatures like bulls, ponies, and donkeys have been supplanted by driven hardware in present-day motorized farming [21].

C. The invention of modern weather forecasting was one of the 19th century's achievements. The widespread use of portable engines and threshing machines added to agricultural growth.

D. Borlaug pioneered a new irrigation and crop management system that enabled plants to thrive. When mainstream new wheat assortments were made accessible in nations everywhere during the 1960s, the upsides of what was named the "Green Revolution" became clear. Later, white insurgency, yellow, and biotechnology upsets have to a great extent affected the agriculture areas [5].

E. Huge improvements in farming innovation happened during the 20th century, including the development of manufactured compost and pesticides, as well as present-day rural apparatus like mass-created work vehicles and rural airplanes for flying pesticide application. Horticultural plastics, hereditarily adjusted harvests, improved trickle water systems, and soil less cultivating methods are among the latest advancements.

F. Now let us deep dive and explore the technological advancements in the 21st century. Information Age innovations were gradually applied to agriculture in the first decades of the twenty-first century. Agricultural robots, drones, and self-driving tractors have all become commonplace on farms, whereas digital agriculture and precision agriculture make extensive use of data collection and computation to increase farm productivity.

5. How Is the Internet of Things?

The Internet of Things (IoT) is a network of electronic, software, sensor, and connectivity-enabled devices that can communicate, interact, and exchange data. The IoT device in this example does not need to be linked to the Internet. Adapting to the IoT method provides farmers with two distinct advantages. It has aided farmers in lowering costs and increasing crop yields.

6. IoT Helpful to Agriculture

By and large, the Internet of Things (IoT) alludes to gadgets that trade data and can work with each other over the web. Agribusiness IoT is a subset of the IoT space that centers around gathering subsets of the IoT space that centers on gathering information on harvests and animals, assessing their wellbeing, and settling related issues more successfully than relying on human criticism.

In horticulture, the critical part of IoT is to present a circle of check, dynamic, and mediation. In the first place, connected sensors gather information on the condition of a yield. The enormous amounts of information are consolidated into an organization that ranchers can use without much of a stretch. Increased execution is the conspicuous result. Ranchers may settle on instructed crop treatment choices on the off chance that they have applicable information readily available consistently. They will figure yields and work costs ahead of time.

Since IoT is firmly connected to robotization, it needs fewer humans in the form of representatives. Cultivating turns out to be more worthwhile because of higher harvest yields and lower work and coordination costs. The little family farms, natural ranches, and even housetop nurseries will profit from IoT selection, which isn't simply valid for enormous scope of cultivating tasks.

7. Role of IoT in Farming

Smart farming is a concept that uses IoT technology to boost agricultural productivity. In IoT-based smart farming, a device for monitoring the crop field with the help of sensors (soil moisture, humidity, temperature, light, etc.) and automating the irrigation system is installed [14].

Smart farming is a modern farming management method in which farmers can efficiently use fertilizers and other tools to increase the quality and quantity of their crops. It is difficult for farmers to be physically present in the field at all times of the day. Farmers can often lack the expertise necessary to use various methods to determine the optimal environmental conditions for their crops. The IoT gives a robotized framework that can work without human supervision and can caution them to take suitable action in response to various types of problems they may encounter while farming. It has the ability to contact and alert the farmer even when he or she is not in the field, allowing the farmer to control more farmland and increase production [23].

8. Applications

A. Precision Farming: The key to advanced rural development is an increment of inefficiency for every unit of land. Precision cultivating, otherwise called exactness horticulture, can be

> portrayed as whatever makes cultivating more controlled and exact, particularly with regards to developing crops and raising domesticated animals. It can help ranchers get more exact information about, say, the kind of seeds utilized, the measure of seeds utilized, supplements, compost, and water system per unit of land. Ongoing information from sensors, gear, climate, control frameworks, advanced mechanics, self-governing vehicles, mechanized equipment, variable rate innovation, water, GIS, and GPS can assist with land investigation, supplement esteems, dampness, water system or waste necessities, and arranged versus real harvest yields, in addition to other things.

Exactness horticulture is portrayed by the appropriation of the fast web, cell phones, and precise, minimal-cost satellites (for symbolism and situating) by the makers, to give some examples of essential technologies. Precision agriculture is quite possibly the most notable IoT application in the agrarian field, and numerous organizations use it all over the world.

Harvest Metrics is an exacting farming organization that spotlights the forefront of agronomic arrangements and works with accuracy with the executives. It gives information on crop strengthening and broadening. Crop Metrics items and administrations incorporate VRI streamlining, soil dampness tests, and the virtual analyser PRO, among others. VRI (Variable Rate Irrigation) enhancement improves yields and builds water use effectiveness in updated harvest fields with geography or soil heterogeneity. The soil dampness test innovation offers full in-season neighbourhood agronomy help as well as suggestions for water use execution advancement. The virtual streamlining agent PRO coordinates different water executives' advancements into a solitary, cloud-based, and productive area for specialists and cultivators to exploit accurate water system benefits through a basic interface [13].

Exactness cultivating centers around utilizing assets to support creation and profit from speculation. It gets a good deal on manure and pesticides, stays away from soil disintegration, utilizes water, and lifts efficiency. Accuracy horticulture will upgrade planting practicality, guarantee the best market costs through market information and e-market changes, give compost endowments through direct bank moves that take out or bring down the expense of monetary mediators, and improve farming expansion. When joined with improved seed supply and land and water board, the possibility of increment by twofold can be figured out. Ranchers' pay can increase when improved seed supplies and land and water executives are consolidated, which can bring about two-fold and triple trimming [20, 16].

B. Big Data: Huge information has arisen as a central member in the utilization of innovation to farm the turn of events. Large information is frequently seen in farming as a mix of innovation and examination that can catch and incorporate new information and interact with it in a more valuable and ideal way to help dynamic. This will assist ranchers with utilizing information and settling on better choices, which can prompt astonishing outcomes. Soil testing information may help ranchers decide the normal yield of their dirt, just as the best utilization of manures and pesticides, bringing down their information costs. Big data helps agriculture businesses to improve crop yield, manage risk, and boost productivity. It helps in forecasting the weather, soil conditions, water resource availability, raw input costs, etc.

Precision agriculture's key goal is to ensure profitability, productivity, and long-term sustainability by using big data to direct current and future decision-making. This could include anything from the best time to add fertilizers, chemicals, and seeds. The best location in the field to apply a rate.

C. Artificial Intelligence: The availability of precision data has accelerated the production and implementation of AI in agriculture. AI in agriculture has nearly removed the obstacles to conventional farming, allowing farmers to be future-ready. AI creates an information repository for farmers to rely on by collecting and analyzing data. The agriculture industry enthusiastically and freely incorporates AI into its practices to improve overall performance. Artificial Intelligence is used in a variety of ways on farm machinery. In various areas of a field, ranch apparatus will plant various densities of seeds and apply various amounts of manure. It helps in anticipating warnings for planting, bug control, shower pesticides, inundating, and item valuing will help Indian ranchers increase their efficiency and pay [16, 10].

D. Agricultural Drones: Robots are utilized in horticulture to improve an assortment of cultivating practices. Yield wellbeing assessment, water system, crop review, crop splashing, planting, and soil and field examination are a portion of the manners in which robots are utilized in farming, both on the ground and noticeable all around. Harvest wellbeing imaging, coordinated GIS planning, usability, time reserve funds, and the capacity to expand yields are large benefits of utilizing drones.

SZ DJI Technology Co., Ltd., Aero climate, Precision Hawk, and so forth are a couple of organizations that give robots the ability to gather valuable information through a progression of sensors that are utilized for horticultural and imaging, planning, and looking over. Plant well-being lists, plant checking, and yield expectations, plant stature computation, shade cover planning, field water pounding planning, exploring reports, stock estimating, chlorophyll estimation, nitrogen content in wheat, seepage planning, weed pressure planning, etc. would all be able to be gotten from drone information. During the flight, the robot catches multispectral, warm, and visual symbolism before arriving at a similar location from which it took off [7, 6].

E. Livestock Monitoring: Farmers today face a variety of challenges, including infrastructure, connectivity, increasing demand for animal proteins, food spoilage, and disease, with animal health issues on the rise. On account of tag-checked domesticated animals, programmed taking care of, sheet material, and direct nibbling, the shepherd would now be able to rest under a concealed oak. In the present world, innovation is upsetting each industry, including animal management. Large ranch proprietors can use remote IoT applications to gather information about the area, prosperity, and soundness of their dairy cattle. This data helps them to distinguish creatures that are debilitated so they can be isolated from the crowd, along these lines, forestalling the spread of illness. It likewise brings down work costs as farmers can find their steers with the assistance of IoT-based sensors. There are various organizations engaged in helping ranchers deal with cattle. These companies provide tracking services, and also aid cattle owners in feeding and monitoring their farm animals.

Electronic sensors help automatically observe pregnant cattle on the verge of giving birth or cattle who are suffering from some disease. This hardware can be constrained by GPS trackers, IoT gadgets, and portable applications for idealness and accuracy. When the cattle water splits, a sensor-driven by a battery is ejected. This communicates with the herd manager. The sensor allows farmers to be more concentrated when working with cattle that are giving birth.

F. Smart Greenhouses: Nursery cultivating is a strategy for expanding the yield of vegetables, natural products, and different harvests. Manual interference or a proportional control mechanism are used in greenhouses to regulate environmental parameters. These approaches are less efficient since manual interference results in output losses, energy losses, and labor costs. With the aid of IoT, a smart greenhouse can be created. This design intelligently monitors and regulates the environment, removing the need for manual intervention.

G. Farm Mechanization: Modernized homestead apparatus can be applied for development, planting, showering, manures and pesticides, and reaping, and so forth. Distant controlled sprayers, sowers, and water system gadgets can help change the customary rural practices everywhere in the world.
H. Climate Monitoring: Among ranchers, the IoT for environmental observing is likely the most well-known. Since the gadgets are associated with savvy cultivating sensors, they gather information from the environment and send it to the cloud to plan the environment. Ranchers utilize this data to pick reasonable harvests and make the essential estimations to build crop yields.
I. Smart Irrigation System: In the world, farming is the greatest user of new water. Water is becoming a scarce asset because of worldwide environmental change. It is fundamental to forestall water squander and ideally use water in the most ideal manner. Along these lines, the greater part of ranches starts with a shrewd water system while executing IoT agribusiness. One can save time and give the best therapy to crops by streamlining the timetable and volume of water. Sensor-based IoT advances gather information about soil, update crop status, and send the information to cultivate water system frameworks [2, 11, 12].
J. Automated Farming with Agricultural Bots: Agricultural bots are robots that are specifically programmed to automate agriculture. Agribusiness bots have as of late been utilized in each period of the growing cycle. The agri-bots have made life somewhat simpler for ranchers by burrowing, weeding, preparing, picking, and splashing.
K. Self-Driving Combines: Self-driving combines, also known as ‘Driverless Tractors,’ are automated tractors that can operate independently. Without the intervention of a person within the tractor, they deliver a high tractive effort. While playing out their main goal, they are customized to act naturally mindful, settle on speed, and keep away from hindrances like individuals, creatures, or items in the field.

Any of oneself driving farm haulers work under controlled self-sufficiency. They're computerized farm haulers with a manager and correspondence and control through Vehicle-to-Vehicle (V2V) innovation. AI integration into these self-driving combines ensures application protection while also ensuring that they continue to learn from the self-observational data they collect.

L. Agri-business Management: IoT-based incorporated data climate, with information from fields, transportation organizations, preparing units, markets, and fare houses available on a solitary stage, quality upgrade, cost decrease, expanded benefits, and serious selling costs, in addition to other things.

9. THE IOT TECHNOLOGY

In the coming years, the Internet of Things (IoT) framework is expected to be the most significant change agent in agriculture. Farm managers or farmers may use an IoT system for real-time crop tracking, precision planting, livestock management, and smart greenhouse management, among other things. The IoT technology in agriculture is more efficient for the following reasons:

- Data, enormous heaps of data, assembled by splendid cultivation sensors, for instance, environmental conditions, soil quality, reap improvement progress, or dairy steers' prosperity. This data can be used to follow the state of your business in general, similarly to staff execution, gear capability, etc.
- Better authority over within measures and, therefore, lower creation possibilities. The ability to expect the yield of the creation licenses you to improve resource allocation. If you know accurately how many yields you will gather, you can guarantee your thing won't lie around unsold.

- Cost the leaders and waste lessened by the extended order over the creation. Having the choice to see any irregularities in the gathering advancement or tamed creature prosperity, you will really need to direct the perils of losing your yield.
- Increased business adequacy through measuring robotization. By using splendid contraptions, you can automate various cycles across your creation cycle, for instance, water framework, planning, or bug control.
- Enhanced product quality and volumes. Achieve better order over the creation cycle and keep up better assumptions for gathering quality and advancement limits through robotization.

Hence, these components can at last provoke higher pay [3].

10. Challenges Faced in the Agricultural Sector by IoT

Farmers face several obstacles when it comes to applying IoT in the agri-sector.

- Lack of Infrastructure: Even if ranchers carry out IoT innovation, a feeble correspondence foundation would keep them from exploiting it. Homesteads are arranged in provincial territories with restricted web connectivity. Since a rancher requires solid admittance to edit information consistently and from any website, availability issues will make a high-level observing framework pointless.
- Expensive Equipment: Several cost-related issues happen while executing IoT in agribusiness, like arrangement and working expenses. Equipment costs, like IoT gadgets/sensors, base station framework, and entryways, are remembered for the arrangement costs. Furthermore, working expenses incorporate a consistent

membership for the IoT framework board, information trade, and different offices, as well as unified administrations that offer data/information assortment.

- Lack of innovative knowledge: The greatest test for ranchers living in rustic zones is the absence of information on innovation. This is a typical issue in non-industrial nations, where most ranchers are unskilled. The selection of IoT in agribusiness is a critical test, as it requires a huge interest from ranchers preparing for the sending of the IoT framework.
- Lack of Security: At an alternate degree of IoT-based rural frameworks, security issues arise that should be settled. Clients face various troubles because of helpless assurance, including information misfortune and other on-field boundaries. Actual interruption, like assaults by creatures and hunters, or an adjustment of the actual location, places IoT gadgets in horticulture in danger. Exactness cultivating frameworks, for example, IoT-empowered area data and area-based administrations, are helpless against programmers who could utilize this information to catch gadgets. The IoT PC is assaulted, and cryptographic executions are brought down. Refusal of administration (DoS) assaults and remote sign obstructing are additionally normal in other correspondence layers. Seizing assaults, meeting capturing, information base issues, and disavowal of administration assaults are all significant security dangers to cloud frameworks.

  At the point when IoT gadgets speak with more seasoned gear that has a web network, there is no confirmation that they will actually want to get to ramble planning information readouts utilizing the public web interface. IoT horticultural frameworks amass an enormous amount of information that is hard to get.
- Reliability: Harsh ecological conditions may cause correspondence disappointment and embarrassment of sent sensors. It is critical to guarantee the actual wellbeing of sent IoT Adaptability.

- Scalability: In the horticultural area, countless IoT gadgets and sensors have been introduced, requiring the utilization of a clever IoT board framework to recognize and screen every hub.
- Localization: When it comes to introducing gadgets/sensors, there are a few interesting points. Without sending extra gadgets with overhead design, such gadgets ought to have the option of giving usefulness and administration to the remainder of the world. Moreover, the best organization area should be picked so gadgets can interface and offer data without interference.
- Interoperability: There are billions of IoT gadgets, norms, and conventions that are expected to interoperate. Interoperability includes semantic, syntactic, specialized, and authoritative approaches. More examination work is required to acquire high interoperability among different IoT gadgets [9].

11. How Beneficial IoT Technique in the Agricultural Sector?

a. The whole IoT biological system is comprised of sensors that can dependably follow constant ecological conditions, including dampness, precipitation, temperature, and that's just the beginning.
b. Water stockpiling can be accomplished adequately with the IoT framework, with no water squander because of sensors.
c. The Internet of Things (IoT) framework has permitted climate stations to consequently change environmental conditions dependent on an assortment of guidelines, permitting our nurseries to become more intelligent. The utilization of the IoT gadget in nurseries has diminished the requirement for human obstruction, making the entire interaction savvier while likewise improving accuracy.

d. Soil preservation, for example, pH and dampness content, can be handily recognized, permitting ranchers to sow seeds as per soil level.
e. IoT in agribusiness has helped ranchers to keep up with crop quality and soil ripeness, bringing about expanded item volume and quality.
f. Crop following can be effortlessly accomplished by utilizing IoT to follow the advancement of the yield.
g. The Internet of Things permits ranchers to forestall obstructions and resolve any issues that may happen during the cultivating cycle. Therefore, the item's consistency improves, and clients get an excellent item.
h. IoT advancements look to make the best use of assets like water, power, and property. Exactness cultivating is centered around information gathered from an assortment of field sensors, permitting ranchers to definitely distribute barely enough assets to solitary plants.
i. In farming, IoT gadget frameworks join computerization, for example, request-based water systems, preparing, and robot collecting.
j. The Internet of Things (IoT) gadget helps in the steady checking of the land, so that means can be taken at the beginning phase. It supports efficiency, diminishes difficult work, saves time, and makes cultivating more profitable.
k. The time saved because of the IoT system might be significant. Furthermore, in this day and age, we may all benefit from additional time.

12. Disadvantages of IoT in Agriculture

a. Internet of Things (IoT): Smart agriculture needs constant internet access. These standards are not met in rural areas of developing countries, and internet speeds are slower.

b. The farmer must understand and learn how to use technology in order to use IoT-based equipment. This is the most difficult aspect of implementing smart agriculture framing on a wide scale around the globe.
c. Despite some security steps, the device has little control and can be used to launch a variety of network attacks.
d. Creating, developing, managing, and activating a broad technology to IoT framework is a complicated process.

13. IMPACT OF IOT ON AGRICULTURE

In this Fourth Industrial Revolution, "smart farming" is a perfect way to describe agriculture. What makes agricultural developments so fascinating right now is that the Fourth Industrial Revolution's advances intersect and align with the "Second Green Revolution."

The Internet of Things is ushering in a new age of smart farming, allowing farmers to grow crops in a more regulated and efficient manner, as well as encouraging better land utilization through proper crop selection and enhanced monitoring of soil, temperature, irrigation, plant health, and other critical factors that affect yield.

IoT-based smart farming is designed to track and automate irrigation in crop fields using sensors such as humidity, temperature, and soil moisture. When compared to the traditional approach, IoT is extremely effective [17].

Platforms that can interact and sense precisely calculated environmental data are still being developed by IoT device providers to help boost farm efficiency. Drones, LED lamps, energy storage, transmitters, microcontrollers, and other technologies are used in these IoT platforms. It's designed to help farmers use remote sensors to track vital information like air temperature, humidity, and soil quality, as well as increase crop yields and forecast harvests. One way to increase efficiency and ensure food quality in the supply chain is to use satellite imaging and IoT track-and-trace equipment to control farming operations from harvest to distribution. The Internet of Things system, when combined with Web Map Service (WMS) and Sensor Observation Service (SOS), provides a solution for managing crop irrigation water requirements or supply. It analyses crop water needs intelligently and uses available water supply supplies to minimize waste [1].

In agriculture, the Internet of Things allows for the avoidance of obstacles and the elimination of all problems that may occur during the farming process. As a result, the product's consistency improves, and customers receive a high-quality product. By empowering farmers and growers to cope with the immense obstacles they face, the Internet of Things is changing the agriculture industry like never before. Unexpected environmental shifts, economic downturns, and a variety of other risk factors are likely to have an effect on farmers.

Farmers can benefit from IoT systems in a variety of ways. Sensors can be deployed across farm and farming machinery to enable farmers to gain an abundance of insightful data, such as the amount of fertilizer used, the number of seeds planted, storage conditions, and the status of farming equipment and machinery. Farmers can easily monitor a number of environmental variables and make informed decisions once an IoT system is in place. Farmers will be able to use pesticides and fertilizers more precisely with the aid of smart sensors.

14. Future of IoT in Agriculture

Agriculture is one of the major industries to incorporate technology. Today, technology can solve most of the challenges that farmers face, including soil problems, the environment, irrigation, and supply chain gaps, thanks to increased digitalization. It can assist them in more accurately predicting weather conditions, adopting more sustainable irrigation methods, reducing wastage, and, as a result, enjoying better yields and higher incomes. Farmers can now receive timely alerts, relevant information, and track their crops using something as simple as their smart phones. More farmers are seeing how using solutions that use cutting-edge technology, including Artificial Intelligence (AI), Machine Learning (ML), and the Cloud, will help them improve climate resilience, crop yield, and price control [19].

Smart farming, which is built on IoT technology, allows growers and farmers to minimize waste and increase efficiency in a variety of ways, from the amount of fertilizer used to the number of trips taken by farm vehicles, as well as the effective use of resources like water and electricity.

According to a BI Intelligence survey, the adoption of IoT devices in the agriculture industry will hit 75 million by 2020, increasing at a rate of 20% per year. Simultaneously, the global smart agriculture market is projected to triple in sizeby2025, to $15.3 billion [4].

According to National Geographic, in less than two years, a small farm of 800 acres can earn $11,000 per year, a medium-sized farm of 1600 acres can earn $26,000 per year, and a large farm of 2400 acres can earn $39,000 per year by properly using technology [11].

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Chapter 3

INTERNET OF THINGS FOR SMART FARMING

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ABSTRACT

Amid people's thinking of the farming operation, the fact is that today's agriculture is data-centric, accurate and better than before.

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Nearly every sector, including "intelligent farming," was revolutionized by the rapid advent of Internet-of-Things (IoT) technology, which led the sector from statistical to quantitative solutions. Such innovative advances are changing the current farming practices and posing new obstacles. This chapter provides the importance of wireless and IoT sensors in agriculture as well as the obstacles facing the integration of this technology with conventional agricultural practices. Detailed analysis of crop condition, fertilizer, insect detection and pesticide is carried out on IoT products and wireless sensor connectivity methods in farm applications. This chapter proposes an IoT-based model to alert farmers for soil moisture conditions, potential damage in agricultural land from the fire and automatic water irrigation started at low moisture of soil or fire. Finally, this chapter covers contemporary and future IoT trends in smart farming and research difficulties.

Keywords: Internet-of-Things, smart farming, advanced agriculture practices, soil moisture sensor, fire/smoke sensor

1. INTRODUCTION

Internet of Things (IoT) is the network or web of connected devices. The devices can be computing devices, mechanical or digital devices. Every connected device has a Unique Identifier. When two or more objects can communicate (send and receive signal or messages), a communicating network is created between these objects. That network between objects is called the Internet of Things.

Basically, we can say that when the power of the Internet is extended from a computer and mobile phones to other household devices, it is called *Internet of Things*. IoT has changed today's world Living and Working style. All the devices present in the surrounding can become smart devices when IoT is implemented on that. Many concepts have already been developed and are working with good outputs. Such as Smart homes, smart cities, smart cars, smart factories, etc., are some of the concepts that are being used these days[1].

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[1] +DTXH HW DO 3$Q ,R7-Based Model for Defending Against the Novel Coronavirus (COVID-19) 2XWEUHDN ´

Any cropland with fire detection sensors to send alert message to farmer or any home with smart door lock sensor are example of Things in IoT[2]. Due to this feature, it has applicability in various fields. Figure 1 shows some of its application areas.

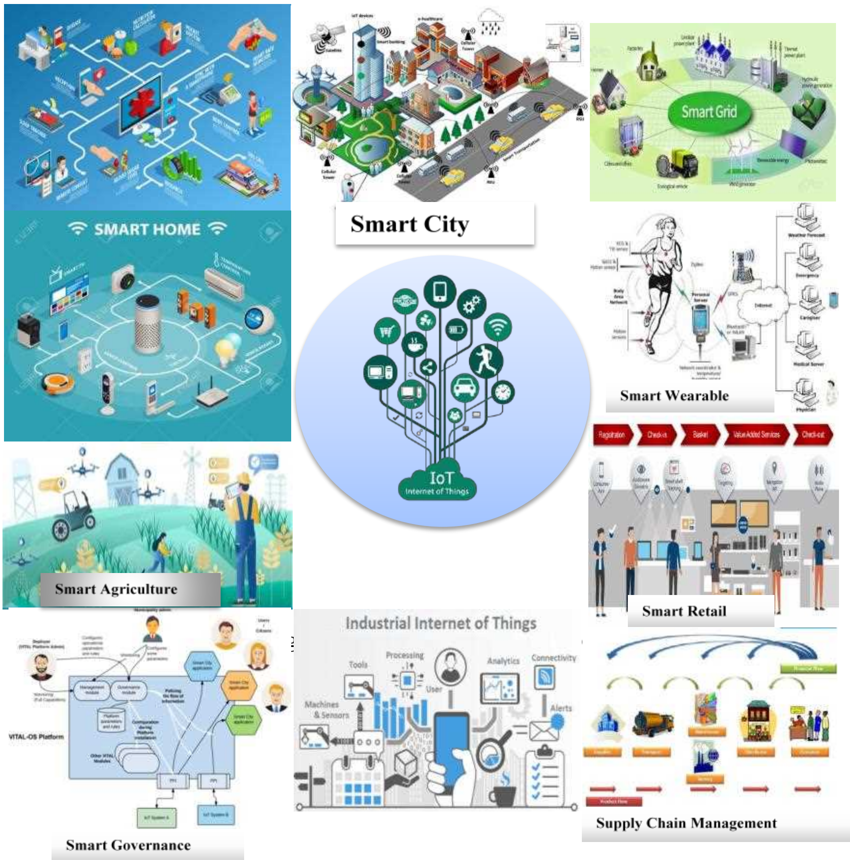

Figure 1. IoT Applications.[3]

Keeping these features of IoT in mind, this research paper has been written to apply these in the agriculture field. Therefore, the main objective of this research is:

[2] Haque et al.

[3] Haque et al., "A Comprehensive Study of Cyber Security Attacks, Classification, and Countermeasures in the Internet of Things."

- To make agricultural techniques used in India advanced with the help of IoT.
- To increase the productivity of agriculture.
- To protect the crop destruction from fire in cropland.
- To make farmers up-to-date with the use of the latest technology.

The remainder of this chapter is arranged accordingly. Section 2 reviews the literature. Section 3 briefly details the IoT Ecosystem. Section 4 and 5 deal with IoT agriculture and its structure including the components. Section 6 smart farming with IoT. Section 7 methodology and proposed model. Section 8 deals with limitation and section 9 discusses future scope in the product with advancements in IoT. Lastly, section 10 concludes this chapter.

2. LITERATURE SURVEY

B. Ragavi et al.[4] proposed the "AGROBOT" model for monitoring weather, fertilizers and status, and water requirement, which was based on AI and IoT. This model improves the crop yield with low cost. Shibin David et al.[5] proposed a model, which used AI and Ardunio UNO for measuring pH, temperature, and wetness of varied soils are all aspects to consider. All measuring values can be accessed through the GSM module. This model increased the production of crops. Deepak Sinwar et al.[6] used IoT, AI Cloud Computing, and Arduino Raspberry Pi and proposed a CS-HYSIS system. D. Sivaganesan [7] predicted soil moisture and plant growth pestilence assault, climate change and time for harvest in a small part of the land.

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[4] Ragavi et al., "Smart Agriculture with AI Sensor by Using Agrobot."

[5] David, Anand, and Sagayam, "Enhancing AI Based Evaluation for Smart Cultivation and Crop Testing Using Agro-Datasets."

[6] Sinwar et al., "AI-Based Yield Prediction and Smart Irrigation."

It also forecasts when and how to apply fertilizers to the irrigation crops and the right moment. Sunil Kumar[7] used ML and Drone technology and using AI and IoT frameworks. By analyzing previous behaviors, he proposed a new irrigation model using sensors and ML algorithms. He also spoke about water conservation, optimal seeding, crop rotation, and time for harvesting. Including temperature sensor, moisture sensor, GSM module, Wi-Fi module, Arduino UNO module, and web servers, B.Vidheya Raju[8] introduced a low-cost farm-field surveillance system. R. Divya et al.[9] proposed "SATURAS" and Stem Water Potential (SWP) system. It is low-cost technology for farmers because one or two sensors are used per hectare. Siddhant Kumar et al.[10] presented a new system based on gCrop that is IoLT (Internet of Leaf Things). The picture of a camera embedded in an ultrasound sensor is collected to monitor growth using sensors in real-time. For observing the growth trend, ML model data collected by sensors is used. By measuring the length of the leaves, the device calculates the age of the leaves. 98% accuracy in the identification of leaf formation, health and maturity, and thus the improvement in crop quality and yield. S. S. Mane et al.[11] presented a GSM-based Automatic Irrigation System. The upper and lower soil moisture parameters can be set in this model. The automatic greenhouse control system for crop production was introduced by K. Radha Gowri[12] in conducting the use of sensors under favorable conditions. It is useful in that the labour cost of smallholder farming and offers a safer farming atmosphere than open farming.

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3. IoT Ecosystem

The Internet of Things ecosystem is difficult to describe. Due to the vastness and evolving possibilities and the rapidity with which it is spreading across the entire market, it is very hard to define its picture. The IoT ecosystem, on the other hand, is a collection of various types of devices that sense and evaluate data and communicate with one another through networks.

The client in the IoT ecosystem has smart devices such as tablets, smartphones, sensors, and other devices to communicate commands or requests for information to various devices through networks. After being evaluated, the system responds and executes the command to send information back to the user through networks.

The four main components of IoT are:

- Low power embedded system: Designing of IoT-based electronic system includes high performance and low consumption of battery.
- Cloud computing - In IoT embedded system, data generated from the devices are stored on reliable storage servers, that is cloud computing.
- Availability of Big Data: Since IoT Technique is heavily reliant on real-time sensors. As a result, the use of electronic devices has spread into every area, resulting in a huge data flow.
- Network connection: Internet networking is required for communication, and each physical entity is assigned an IP address. These addresses are used to create a network link between the devices.

The picture of a typical IoT ecosystem is depicted in Figure 2 given below, in which smart devices send and receive data from other smart devices in the surroundings through network and cloud computing.

The Internet of Things is a network of data transfer devices in and of itself. However, it also has a lot of links to Cloud Computing and Big Data.

- Sensing, Embedded Processing, and Connectivity: Any IoT ecosystem senses its environment, such as pressure, temperature, and gyroscope, and uses devices to perform embedded processing. These devices communicate over networks using any form of system, such as GPS, Wi-Fi, RFID, and so on.
- Technology, Software, and Application: To communicate and interact with smart devices and the world, this ecosystem uses a variety of software, technologies and applications.
- Smart devices and environments, Cloud Computing, Big Data: Data received or transferred from IoT embedded devices and environments is communicated via Cloud Computing or other Servers. This data is stored as Big Data.
- Users or communities: The IoT ecosystem's products and services are used up by users or populations to help them live smarter lives.

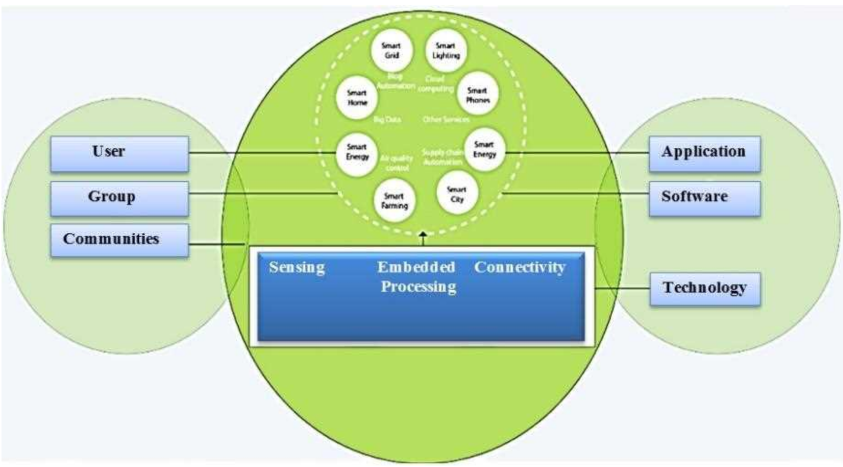

Figure 2. IoT Ecosystem.

3.1. Advantages of IoT

1. Efficiently resource utilization: If we comprehend the characteristics and how any system operates, we can enhance sustainable resource utilization and track natural resources.
2. Minimalize human work: IoT devices minimize our labor by connecting and communicating with one another and doing a range of functions for us.
3. Save time: It undoubtedly saves time by minimizing energy input. Time is the most essential thing that can be saved by utilizing an IoT platform.
4. Enhance Data Collection: As devices in IoT continuously communicate with each other so data is always shared by them which enhance the data collection.
5. Improve security: We can make our system secure if we have connections between everything in that system.

3.2. Disadvantages of IoT

1. Security: In IoT systems, all the devices are interlinked and connected to communicate with one another. Even with several safekeeping measures, the device provides control and can be used to launch different sorts of network attacks.
2. Privacy: Even though the users don't keenly play a part, the IoT structure offers widespread personal data in great detail.
3. Complexity: It is very tough of planning, building, managing, and enabling a broad technology in IoT systems[13].

[13] Haque et al., "A Comprehensive Study of Cyber Security Attacks, Classification, and Countermeasures in the Internet of Things."

4. IoT in Agriculture

The Internet of Things has the potential to change people's lives around the world dramatically. In just a few years, the world's population would have surpassed 3 billion. As a result, the agriculture industry must accept IoT to feed such a large population. Extreme weather conditions, weather change, and various environmental effects resulting from agricultural activities are all problems that must be addressed to come across the demand for more food.

The future of Indian agriculture must be shaped by a thorough understanding of and excessive reliance on technologies that can increase productivity while also regaining farmers' interest in the industry. As a result, these smart farming practices would support farmers to reduce scrap and increase capacity. It is a high-technology-based, capital-intensive method for mass-producing crops in a sustainable manner. Farmers may use this technology to track agricultural land situations from anywhere using sensors and irrigate fields using an automated device. It is the use of ICT (i.e., information and communication technology) in agriculture. Figure 3 shows the use of IoT in Smart Farming.

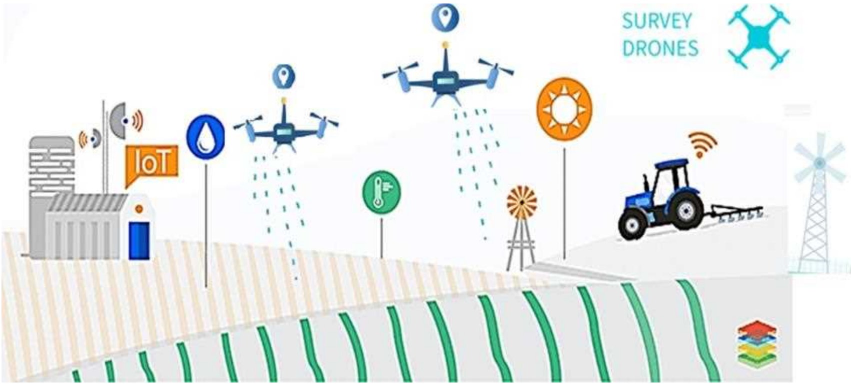

Figure 3. Smart Farming.

5. Structure of IoT in Agriculture

The sensor layer, transport layer, and application layer are the three layers that make up this device structure, and the functions of these layers are mentioned below.

5.1. Sensor Layer

One of this layer's challenges is to obtain automated and real-time transformations of real-world agricultural processing figures into digital transformations or details that can be processed in the virtual world using various methods. The data that are collected are:

- Sensor information: Senses data about humidity, temperature, pressure etc.
- Products information: fetches data about name, model, price and features.
- Working condition: get data about operating parameters of different equipment, apparatus etc.
- Location information

The main goal of the Information Layer is to spot various types of information or data, collect the information and marking information in the real world using sensing techniques, and then remodel them for processing into digital data. RFID tags, sensors, two-dimensional code labels, and sensor networks are some of the techniques used in this sensor layer.

5.2. Transport Layer

The role of this layer is to gather and summarize agricultural data for processing from the previous layer (Sensor Layer). It is thought to be the IoT's nerve center. This layer contains a telecommunication operations center and an internet network, a data center, and smart processing centers.

5.3. Application Layer

This layer aims to examine and process the information collected for the cultivation of digital knowledge of the actual world. It's a hybrid of the Internet of Things and agricultural business intelligence.[14]

6. How IoT Can Be Used for Smart Farming

Precision agriculture is another phrase for smart agriculture. Farmers can improve yields by employing minimal resources such as water, seeds, and fertilizer in this type of farming. By placing sensors and mapping their fields, farmers will be able to gain a micro-level understanding of their crops, save resources, and mitigate climate impacts.

The role of Sensors is very important in Smart Farming. IoT can be used for Smart Farming with the help of various Sensors and Controllers. Following are some sensors that can be used in Agriculture for Smart Farming:

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[14] Parashar, *Candidate Declaration "Iot Based Smart Agriculture Monitoring System."*

- Location Sensors – These sensors measure latitude, longitude, and altitude to just a few feet using GPS satellite signals. To triangulate a location, at least three satellites are needed. Precision agriculture relies heavily on precise positioning.
- Optical Sensors – Light is used to test soil properties in these sensors. Varying wavelengths of light reflectance are scanned using sensors in the near-infrared, mid-infrared, and polarized light bands. Sensors can be used on vehicles, aerial platforms like drones, and even satellites. Just two examples of variables that can be aggregated and evaluated are optical sensor data on soil reflectance and plant color. Optical sensors may be used to measure clay, organic matter, and soil moisture content. As shown in Figure 4, Vishay has hundreds of photo-detectors and photodiodes, which are the fundamental components of optical sensors.
- Electrochemical Sensors: These sensors provide crucial data for precision agriculture, such as pH and soil nutrient levels. Unique ions in the soil are detected by sensor electrodes. Sensors mounted on specially built "sleds" are currently used to collect, process, and map soil chemical data.

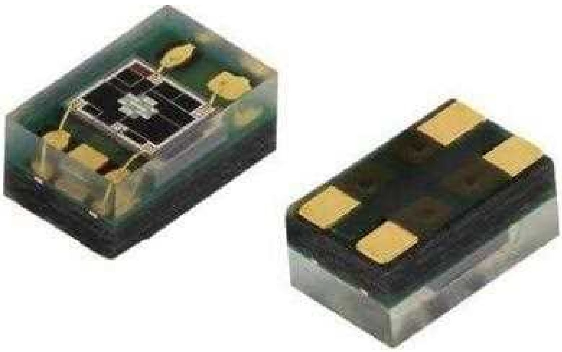

Figure 4. Vishay Photo IC Sensor.

- Mechanical Sensors: Soil compaction, or "mechanical resistance," is measured by these sensors. The sensors use a probe that penetrates the soil and uses load cells or strain gauges to record resistive forces. A unique methodology is employed on big tractors to forecast the pulling requirement of ground-engaging apparatus. As shown in Figure 5, tensiometers, such as the Honeywell FSG15N1A, are extremely useful for irrigation since they monitor the forces exerted by the roots in water intake.
- Dielectric Soil Moisture Sensors: By measuring the dielectric constant (an electrical property that varies reliant on the amount of moisture available), this sensor determines the quantity of moisture in the soil[15].
- Airflow Sensors: The air permeability of the soil is measured by this sensor. Measurements may be taken at specific locations or in real-time when moving. The pressure needed to force a predetermined amount of air into the ground at a specified depth is the desired performance. Unique identifying signatures are generated by a variety of soil properties and soil type, compaction, construction, and humidity level.
- Agricultural Weather Stations: Agricultural Weather Stations are self-contained units that are located in rising fields at different locations. These stations have a mix of sensors that are suitable for the yields and weather in the region. Data related to air temperature, rainfall, soil temperature at various rock bottom, the wetness of leaf, wind speed, relative humidity, solar radiation, wind direction, and atmospheric pressure are collected at scheduled intervals. This data is collected and wirelessly transmitted to a central data logger at predetermined intervals. Because of their portability and low cost, weather stations are appealing to farms of all sizes[16].

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[15] Giordano et al., "IoT Solutions for Crop Protection against Wild Animal Attacks."

[16] Journal and Engineering, "Smart Crop Protection System from Animals and Fire Using Arduino."

Figure 5. Honeywell Force Sensor.

7. METHODOLOGY

This section will describe the proposed model along with its block diagram, flow chart, circuit connection diagram, and program coding for this model.

7.1. Proposed Model

One of the Use Cases of IoT in Smart farming can be when the soil moisture sensor reads the soil's moisture level and automatically switches on the water motor. Whereas, temperature sensor reads the temperature near the crop field and sends this detail to the farmer's mobile. So that farmers can take necessary action if the temperature is adverse for a crop. The smoke sensor can also be used in the field so that if there is an accidental fire in the field, the message can be sent to the farmer on mobile and automatically water sprinkler can be switched on in the field to extinguish the fire[17].

[17] Haque et al., "Security Enhancement for IoT Enabled Agriculture."

Figure 6 is given below in section ‘a’ that describes the block diagram of the proposed model for this Use Case. In section ‘b’, the flow chart is given to describe the flow of logic in the system. In section ‘c’, the required Arduino coding is given for soil moisture sensing to upload on Arduino UNO Microcontroller.

a) Block Diagram of Proposed Model

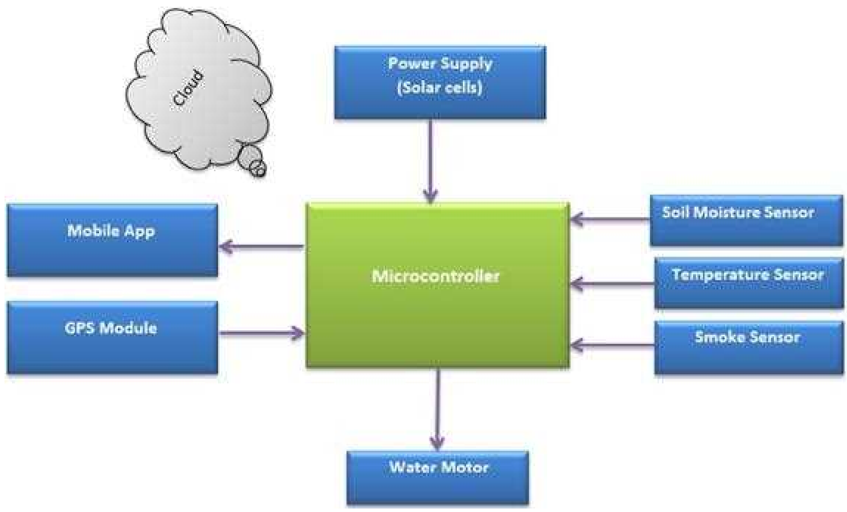

Figure 6. Block Diagram.

b) Flow Chart

The given flow chart shows the flow of logic for the given system, which describes how the data from various sensors is read by a microcontroller and how these data are processed and an output signal is sent to output devices attached.

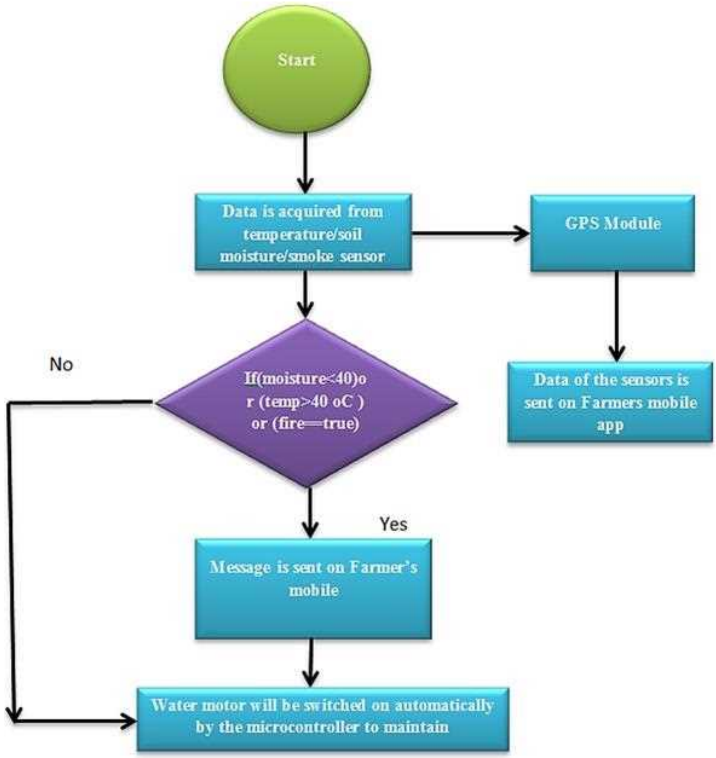

Figure 7. Flow Chart of Proposed Model.

c) Arduino Code for soil moisture sensing along with circuit diagram

i. Circuit connection for soil moisture sensor with Arduino UNO microcontroller and depicting Pin setup for Arduino and moisture sensor is given in Figure 8.

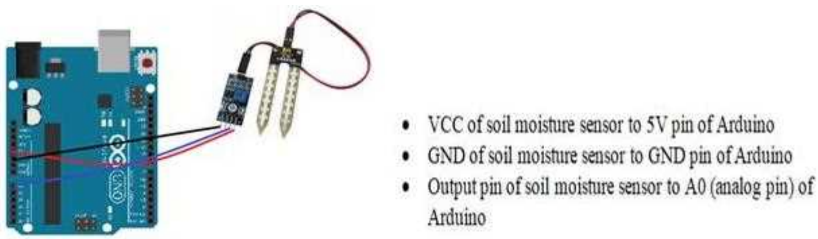

Figure 8. Circuit Connection between Arduino UNO and Soil moisture sensor and Pin Setup for Arduino.

ii. Coding for Working of Soil Moisture Sensor

Coding given in Figure 9 will sense and measure the moisture level in soil and will display the value on the Serial Monitor of Arduino. We can read the data value of the soil moisture sensor from the sensor analog pin and store the values in the "output_ value" variable in the loop function. Since moisture is calculated in percentages, we can map the OUTPUT values to 0-100. When we took readings from the dry soil, the sensor value was 550, and when we took readings from the wet soil, it was 10. So, to get the moisture, we mapped these values. These values were then printed on the serial display.

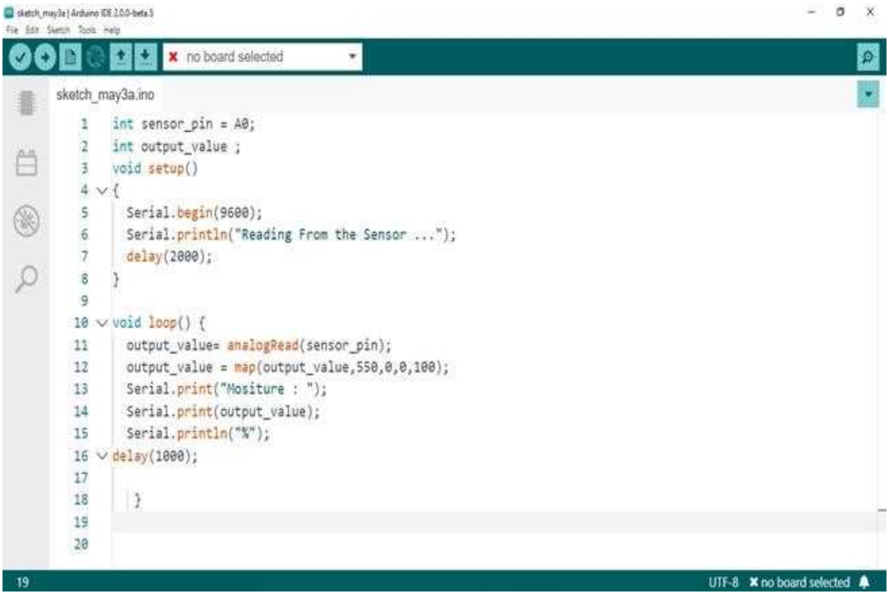

Figure 9. Coding for sensing Soil Moisture sing Sensor and Arduino UNO.

8. LIMITATIONS

As we know, everything in this world has some limitations, so this model too. Following are some of the limitations of this model:

- Cost-effectiveness: This model may cost high for the farmers. As in India, the economic condition of farmers is very bad so they might feel it costly to assemble in their fields.
- Lack of Infrastructure: For assembling this model, basic infrastructure is needed for an internet connection. In our country, many far areas of cropland don't have reach to these infrastructures required for this model.
- Lack of security: This IoT-based model has to communicate with older devices. So sometimes the connection issues may come and security-related issues arise.

9. Future Scope

As we know, India is an agro-based country. A significant part of the population is working in this primary sector of agriculture. But the contribution of agriculture in National Income is lowest of all three sectors. So there is a tremendous future scope of IoT application in Smart farming so that the output from this sector can also be maximized and it gets added to the Gross National Income of the country. This proposed model can also be enhanced by applying a weather monitoring system to it to monitor the weather and alert farmer before any unwanted weather conditions.

Conclusion

Farmers face huge agricultural challenges, including irrigation, accurate knowledge of soils, proper time of use of pesticides, crop diseases forecasting, cost of machinery implementation of the new system, demand & supply of crops and, above all, professional experiences among farmers, advantages and adverse effects of crops, farmers' needs are highly sensitive to farming. Technology plays a vital role in combining farming infrastructure with modern technologies and strategies to solve these problems. Some papers in this chapter were analyzed and it was observed that IoT productivity in agriculture could be used. IoT-based smart farming is definitely a high-tech use of ICT which can be proved as a milestone in securing the crop and increasing the productivity from agriculture. Furthermore, the proposed IoT model will help the farmers to become financially strong and help them to monitor their land from remote areas also.

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Chapter 4

A COMPREHENSIVE REVIEW ON INTELLIGENT SYSTEMS FOR MITIGATING PESTS AND DISEASES IN AGRICULTURE

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ABSTRACT

In the Indian economy one of the most vital and important sectors is agriculture. Over 70% of rural area people depend on agriculture and it is the primary livelihood for them. India is the largest producer of oilseeds, pulses, rice, wheat, sugarcane, and cotton. The economic growth of a farmer completely depends on the quality and quantity of the crop yield. India has diverse agro climatic conditions ideal for growth of various pests and diseases and crops are prone to various biotic (pests and diseases) and abiotic (nutrients, weeds etc.) stresses which leads to poor quality or loss in yield. These pests and diseases cause considerable damage in the growth of the crops. Crops worth Rs

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50,000 crore are lost owing to pest and disease attacks. Therefore, protecting the crop from these stresses is utmost important to get higher yields. Pests and disease identification and application of appropriate pesticides play an influential role in the field of agriculture. Under NARS (National Agricultural Research System) several technologies developed to mitigate this situation. Timely advisories always help the farmers to take up relevant control measures and decrease the crop losses due to pests and diseases. However, there exists a large discrepancy in reaching the technology to farmer's field level owing to the weak extension system. Presently extension to farmers ratio is far less than the recommended (rainfed - 1: 1000 irrigated -1:1200, Hilly regions -1:400). Fortunately, recent advances in information technology paved a way to bridge this gap in the form of developing intelligent systems which helps the farmers to access the information in time for proactive mitigation of pests and diseases. Intelligent systems encompass the knowledge acquisition, synthesis and analyze, predict/identify the pests/disease by integrating advanced technologies such as computer vision and Artificial intelligence. This chapter outlines about intelligent systems, the studies aimed to develop intelligent systems for identification pests and diseases and current literature with proposed solutions in the form of information technology through Internet of Things (IoT), image analysis, machine learning, AI algorithms, and cloud services.

Keywords: AI algorithms, deep learning, Image analysis, disease management, mobile advisory

1. INTRODUCTION

In India, agriculture plays a vital role and 70% of the population depends on agriculture for their livelihood. The application of new technology has allowed human civilization to produce enough food to satisfy the needs of over seven billion people. However, several factors, including pests and diseases, continue to pose a danger to food security [1]. As per the survey of the United Nations Environment Programme (UNEP) plant diseases are a major threat to farmers especially smallholder farmers, who primarily depend on healthy crop production, account for 80% of agricultural production. As a result, accurately recognizing a disease when it first occurs is a critical step towards effective pest/disease management and conventional approaches to pest/disease identification are carried out by a large team of experts. This necessitates a huge team of specialists as well as constant plant surveillance, all of which come at a high cost when dealing with large farms. Farmers, on the other hand, lack adequate facilities or even the knowledge of how to reach experts. As a result, consulting experts is both expensive and time-consuming. Recently, intelligent methods have proved to be useful in controlling vast fields of crops in certain environments. It is quicker and cheaper to diagnose pests/diseases automatically by simply looking at the signs on the plant leaves and providing relevant advisory on pest management or pesticides to control.

Humans are attempting to merge a real brain with an artificial brain as technology advances in this modern age. Artificial Intelligence (AI) was born as a result of this ongoing science. It is the process by which we can build an intelligent machine. Artificial Intelligence is a branch of computer science that can understand its surroundings and adapt to improve its chances of success. AI should be able to carry out tasks dependent on previous knowledge. Deep learning (DL), Convolutional Neural Network (CNN), Artificial Neural Network (ANN), and Artificial Learning are examples of areas that improve machine performance and aid in the development of more advanced technologies. Medical science, education, banking, agriculture, business, defense, and a number of other fields have all been influenced by AI. AI implementation necessitates a machine learning process. This leads us to the AI sub-domain of "machine learning." Machine learning's main goal is to feed the machine with data from previous encounters as well as statistical data so that it can accomplish the task at hand. Today's technology also includes data processing based on previous data and practice, speech and facial recognition, weather predictions, and medical diagnostics. As a result of machine learning, the areas of big data and data science have exploded in popularity. Machine learning is a method for creating intelligent machines that is based on statistical approaches. While there are numerous methods for detecting and classifying plant pests/diseases using automatic or computer vision, research in this area is still lacking. Furthermore, no commercial options exist, with the exception of those that deal with plant species identification based on photographs of leaves. Deep learning is fast gaining traction as the go-to method for image recognition. The biggest challenge in using this approach to automatically identify plant pests/diseases is a lack of image sources that can reflect the vast range of conditions and symptom characteristics encountered in operation. While data augmentation techniques reduce the impact of this challenge, they are unable to replicate the majority of the functional diversity.

Among machine learning methods the most popular method is Deep learning, also known as deep neural networks, has been used successfully in a variety of fields. For example, it creates a link between an input and an output. It takes a picture of a diseased leaf, and maps the leaf-disease pair. A neural network's nodes contain mathematical functions that take numerical inputs from the incoming edges and essentially map numerical output to the current edge. It uses a sequence of stacked layers to map the input layer to the output layer. To strengthen the training process, deep learning models are learned by tuning network parameters. Deep learning algorithms have been used in image and video recognition, recommender networks, and natural language processing, among other uses. For automated plant disease detection [36], deep learning models are becoming the mainstream picture classification techniques. Agriculture is an important part of the economy of every world. South Korea, China, and North America are now investing trillions of dollars in food development and advanced technological deployment. The population is increasingly increasing, and the increase in food demand is directly proportional. India has a wide variety of food crops and, most importantly, species. Agriculture is one of the most fragile industries of the Indian economy, as it underpins all others and has far-reaching consequences. Automation in agriculture is becoming increasingly relevant as technology advances [35] in other industries. Agriculture will become more important as the human population grows, and agri-technology and precision farming will become more important in today's world. This is also known as automated agriculture, and it refers to the use of high-tech computer systems to track weed recognition, seed prediction, yield detection, crop production, and pest/disease detection, among other things.

The chapter's outline includes a brief description of Intelligent Technologies in Agriculture in section 2. In section 3, a comprehensive review was presented, followed by sections 4 which focused on disease prediction of leaf diseases and weed identification. The final remarks are found in Section 5.

2. Intelligent Technologies Applied in Agriculture

This section provides an overview of agriculture-related intelligence technologies. The technologies employed in the literature are machine learning, deep learning, and IoT are briefly explained below.

2.1. Machine Learning

The term Machine Learning was first coined by Arthur Samuel in 1959. He stated that "it gives computers the ability to learn without being explicitly programmed." Further, Machine learning is a branch of artificial intelligence (AI) that learns from the given data without being programmed. Broadly, Machine learning is classified into supervised and unsupervised learning.

2.1.1. Supervised Learning

Supervised learning is one of the most important and popular learning techniques. In supervised learning, the algorithms learn from a labelled dataset and are designed to learn by example. In supervised learning, each instance is a pair consisting of a set of input features and a desired output label called class label. A supervised learning algorithm analyzes the training data based on the class label and correctly determines the class labels for unseen instances. Supervised learning is further classified into two categories of algorithms:

- Classification: A classification problem is when the output variable is a category.
- Regression: A regression problem is when the output variable is a real value or continuous.

2.1.2. Unsupervised Learning

Unsupervised learning is a machine learning model in which training datasets are not associated with class labels. Instead, the models itself learn from the hidden insights present in the data. The training data will have input data but with no corresponding output labels. The goal of unsupervised learning is to group that data based on the data similarities.

- Clustering: Clustering method groups the data instances into clusters or groups based on the similarities.
- Association: An association rule is an unsupervised learning method which is used for finding the relationships between variables in the large database.

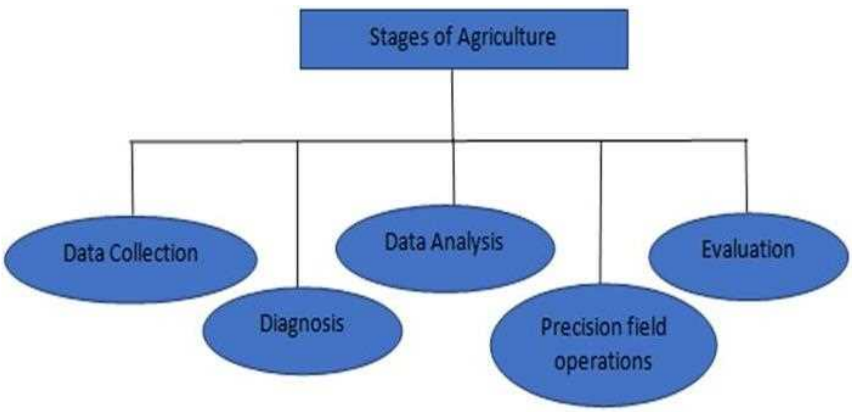

Figure 1. Machine learning application at various stages of agriculture.

The application of Machine Learning in agriculture includes weed prediction, leaf disease detection, crop quality detection, and many more. Figure 1 presents the various stages of agriculture for machine learning application.

2.2. Deep Learning

Deep learning, also known as deep neural networks, was influenced by the functioning of the human brain, emulating dynamic tasks like pattern generation, perception, learning, and decision making. The human brain is made up of billions of neurons that interact with one another and process information. DNN, on the other hand, is a generalized model of the structure of a biological neural network. A number of nodes are arranged in multiple layers including the following:

1. An input layer where the data is fed into the system,
2. One or more hidden layers where the learning takes place, and
3. An output layer where the decision/prediction is given.

They are a relatively new area of machine learning research that enables computational models with multiple computing layers to learn complex data representations at multiple levels of abstraction using multiple computing layers. One of the main advantages of DL is that the model can perform feature extraction in certain cases. DL models also significantly improved the state-of-the-art in a variety of industries and economies, including agriculture. DNNs are nothing more than an ANN with many opaque layers between the input and output layers, and they can be supervised, partially supervised, or even unsupervised. The convolutional neural network (CNN) is a popular DL model in which feature maps are derived by conducting convolutions in the image domain. Deep Boltzmann machines, deep belief networks, and auto-encoders are examples of popular DL architectures. Deep learning was successfully applied in agriculture and Figure 2 presents in general Methodology for Disease prediction using Deep Learning.

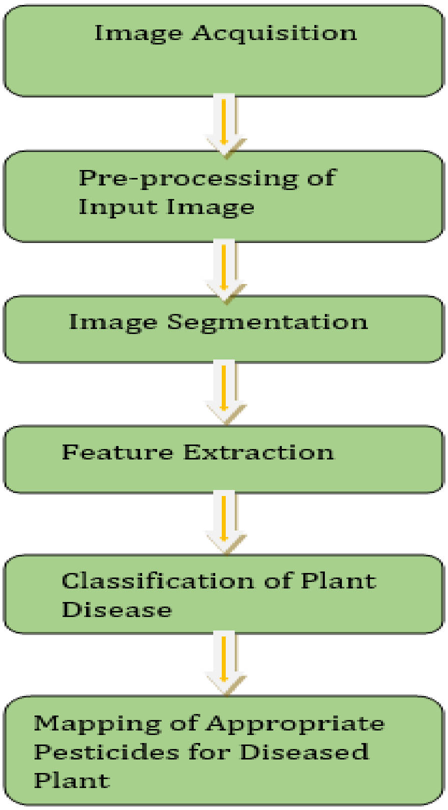

Figure 2. Methodology for Disease prediction using Deep Learning.

2.3. Internet of Things

The Internet of Things (IoT) was first proposed in the late 1980s and has since spread to nearly every area of life. In basic terms, the Internet of Things (IoT) is the network of smart devices and sensors that communicate (sends/receives data) over a wireless communication channel. IoT is a technology in which things can be linked in a network via wired or wireless mode as an entity with a unique identifier and communicate with one another through data transmission over the internet network without the need for human interference. Agriculture can be achieved in a more intelligent way with the use of IoT to enhance productivity, business competitiveness, enhance end product efficiency, increase clarity in the production process, and specific resource use, among other benefits in the entire agriculture process. IoT is a technology that will make agriculture more accurate and smart in terms of using resources effectively (only when needed) by placing sensors over the fields that will capture all required parameters (such as soil moisture, humidity, and temperature) using wireless sensor networks, and the collected data will be sent to a base station or cloud where it will be analyzed and used to make more decisions. Figure 3 presents the IoT architecture for agriculture.

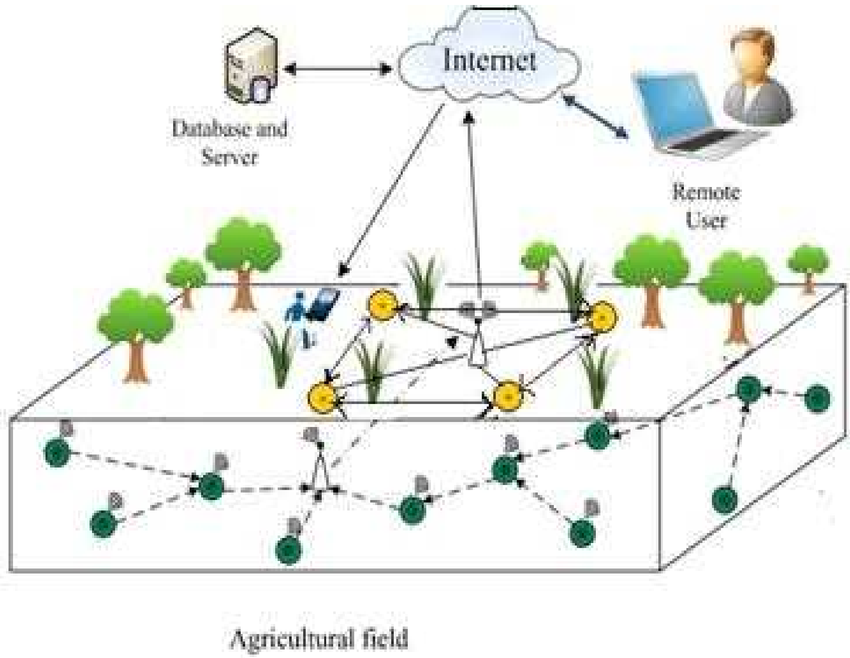

Figure 3. IoT architecture for agriculture.

3. Literature Review

Crop diseases pose a significant danger to food security and productivity. Due to a lack of resources, early detection remains a challenge. Computer vision, cellular networking, and other recent technological advancements have made it feasible to diagnose disease symptoms at an early stage across several geographical areas. Artificial intelligence has grown steadily over the last 50 years as a result of its robustness in implementation and pervasiveness in every area and agriculture is one such sector. Agriculture is a tough sector to manage and it faces multiple obstacles on a regular basis. From seed sowing to crop harvesting, framers face the following main challenges: 1. Infestations of crop diseases 2. Inadequate storage management 3. Pesticide management 4. Controlling weeds 5. Irrigation and wastewater systems are insufficient.

Bannerjee et al. [2] classified AI developments and offered a short description of different AI techniques. From 1983 onwards, computers and electronics began to penetrate this industry. Since then, several proposals and suggested schemes for improving agriculture have been made. Since then, several recommendations and suggested frameworks for improving agriculture have been made, ranging from the database to the decision-making process. Only AI-based systems have proven to be the most practical and efficient since filtering out all other methods. The AI-based approach does not generalize the problem and instead provides a precise solution to a specific complex problem. From the early 1980s to 2018, the literature review covers major breakthroughs in agriculture. The paper addresses more than fifty scientific advances in the agricultural subdomain. The penetration of Artificial Neural Networks and Expert Systems to solve the above problems is discussed first, followed by machine learning and fuzzy logic systems. Finally, it discusses robotics and the Internet of Things (IoT).

Artificial neural networks have been used in agriculture on a number of occasions because of their benefits over conventional systems. The biggest advantage of neural networks is their ability to model and estimate using parallel reasoning. Song et al. [3] combined expert systems and artificial neural networks to forecast crop nutrition levels. When it comes to traditional ES (Expert systems), there are a lot of factors to remember. The use of ANN compensates for all of ES's flaws. The whole machine is based on a single computer chip. When it comes to forecasting strategies, neural networks still come out on top. If a stable set of variables is fed to neural networks, they will predict complex mappings. Robinson et al. [4] created a neural network-based prediction model to address the issue of frost formation in Sicilian fields. The neural network-based prediction model was built by considering data such as humidity, temperature, precipitation, cloud cover, and wind direction to fed into the model first (all these data were taken from 1980 to 1983). The information collected was then translated to binary data. These details have now been split into two sets (input and output for the neural network model). As a neural network predictor, the back-propagation network was used. Initially, the model built and trained a total of ten trial sets. When a range of values for the parameters (mentioned above) were used instead of single values, the frost was predicted more accurately.

Two expert systems for growing cotton crop production were established in less than three years. First and foremost, COMAX. In 1986, Lemmon made a promising attempt to create the Comax expert scheme (COtton Management eXpert). Lemmon, a pioneer in AI in agriculture, developed Gossym, a microcomputer-friendly program that bolsters the use of Comax [5]. For the first time, a computational model (Gossym) was successfully combined with an expert method (Comax) and cotton crop growth was simulated. This expert system was created to work continuously in cotton crop fields during the year. Comax considers three field parameters: irrigation scheduling, nitrogen content in the field, and growth of the crop. Stone and Toman created yet another expert system for the cotton crop (1989) namely COTFLEX. The system was built on a Pyramid 90X machine that ran on the UNIX operating system. The scheme integrated field and farm databases to provide valuable information about the cotton crop to farmers, making it easier for them to take corrective action.

In Texas, the researchers developed the rule-based expert system, which employed modeling models and databases to assist Texan farmers in making smart economic and financial decisions. COTFLEX was installed into an IBM microcomputer and made suitable for usage after successful trials. The SOYGRO soyabean crop growth model, referred to as SMARTSOY in the study, is discussed by the author [6]. A knowledge-based methodology describes the model, which is divided into two approaches: the positivistic approach, which tries to reproduce domain experts' processes in order to arrive at a conclusion, and the normative approach, which tries to repeat the results and attempts to duplicate the findings while removing domain experts' processes.

Prakash et al. [7] created PRITHVI, an expert system built on fuzzy logic, in Rajasthan, India (2013). The machine was created specifically for the Soybean crop. This method drew on the expertise of agricultural officers, written literature, and soybean crop experts to build its knowledge base. PRITHVI was split into five parts. The primary goal of creating this expert framework was to assist local farmers in increasing their soybean yield. As a user interface module, the system used MATLAB. A comprehensive analysis was conducted in the Dehradun valley, with India evaluating the value of incorporating ANN into many techniques for estimating ET. For ET estimation, researchers gathered monthly climate data from the Forest Research Institute (FRI) in Dehradun.

The following techniques were used to apply the algorithms: The Penman-Monteith process is the first along with the Levenberg-Marquardt equation to backward propagation. The number of hidden layers in the system was discovered to allow the ET approximation to become unreliable. As a result, for the overall optimal estimate of ET, a training function with the best trial and error approach should be selected. It was discovered that function training with 75 percent data feed was the most reliable and had the most neurons out of six ANN model training algorithms. There was also a gauging between the PM method and the ANN model using the single layer feed forward back propagation algorithm. The ANN model was created and improved using Matlab. Six different algorithms were created and tested. Given the importance of evapotranspiration in irrigation and water management, this research demonstrated the predictive ability of an ANN structure when used correctly.

In [8] the author presents a comprehensive literature survey on the applications of artificial intelligence techniques in agriculture. Agriculture faces a variety of problems, including disease and insects infecting the field, excessive soil management, insufficient drainage and irrigation, and so on. Owing to the improper use of pesticides, results in significant crop degradation as well as environmental hazards. To address these questions, several experiments have been conducted. Systems are being created to support agricultural experts around the globe in finding better solutions. The review includes 100 significant contributions in which artificial intelligence methods were used to address agricultural problems. They examine the use of artificial intelligence tools in agriculture to provide multidimensional evolution of agro-intelligent systems over the last 34 years, from 1983 to 2017. With the rise of big data technology and high-performance computing, machine learning has opened up new possibilities for data-intensive research in the multi-disciplinary agri-technologies domain. Liakos et al. [1] reviewed various machine learning technologies applied in agricultural production systems. Crop management applications include yield estimate, disease identification, weed detection, flower quality, and species recognition; livestock management includes animal health and livestock processing applications; water management includes water management applications; and soil management includes soil management applications.

4. Disease Prediction

Deep Learning (DL) or deep neural networks (DNNs) are two recent fields of machine learning science. Multiple computing layers make up DL's framework, which allows it to handle complex data representations.

It enables multi-layered computational models to learn dynamic data representations at various levels of abstraction. One of the most significant advantages of DL is that the feature extraction process is often performed by the model itself. DL models also significantly improved the state-of-the-art in a variety of fields, including agriculture. DNNs are supervised, partially supervised, or unsupervised ANNs with multiple hidden layers between the input and output layers. The convolutional neural network (CNN) is a common deep learning (DL) model that generates feature maps by implementing convolutions in the image domain. Common DL architectures include deep Boltzmann machines, deep belief networks, and auto-encoders.

4.1. Leaf Disease Prediction

Leaf diseases are a significant threat to food security, but due to a lack of adequate resources in many parts of the world, early detection is difficult. Recent advances in computer vision and image processing can provide a solution for identifying leaf disease prediction and pesticide recommendation.

In the field of deep learning architecture, a convolutional neural network (CNN) has succeeded in image classification, plant disease recognition, and leaf image classification. In [8], the author proposed a novel CNN model for plant disease detection. The model was able to recognize 13 different plant diseases from the healthy leaves. The deep CNN training was carried out using the Caffe deep learning platform created by Berkeley Vision and Learning Centre. According to the scientist, the evolved model has a precision of 91 to 98 percent for separate class studies, with an average of 96.3 percent. Rather than contemplating the whole leaf, the author investigates the use of individual lesions and spots for the task. The variability of the data is enhanced without the need for additional images because each area has its own characteristics. This also makes it possible to identify different diseases that affect the same leaf. However, appropriate symptom segmentation must also be performed manually, avoiding complete automation. The accuracy obtained using this method was on average 12% higher than the accuracy obtained using the original photographs. Furthermore, no crop had an accuracy of less than 75%, except through 10 diseases were taken into account. Although the database does not cover the full spectrum of realistic possibilities, these findings show that deep learning approaches are useful for detecting and recognizing plant diseases as long as adequate data is present.

Mohanty et al. [9] proposed image-based plant disease detection using deep learning. The proposed model was educated on plant leaf images and classified both crop species and disease presence using deep convolutional neural network architecture. The model was tested on 54,306 photographs from the Plant Village dataset, which included 38 groups of 14 crop species and 26 diseases. The proposed model had a 99.35% accuracy rate. Arivazhagan et al. [10] suggested using image recognition to capture photographs of leaves to diagnose plant diseases automatically. They used texture analysis to detect and distinguish plant leaf diseases on ten different plant species, including banana, beans, jackfruit, lemon, mango, potato, tomato, and sapota, with a result of 94.74 percent accuracy. The author of [11] offers a comprehensive survey of developments in various image processing methods used to study plant diseases and pests.

The author of [12] describes an image segmentation strategy for detecting and classifying plant leaf diseases automatically. They also give a comprehensive overview of the various disease recognition methods used in the diagnosis of plant leaf diseases. The ten species on which the proposed algorithm is evaluated are banana, peanuts, jackfruit, lemon, mango, potato, tomato, and sapota. They said that they were able to achieve the best results in recognizing and classifying leaf diseases with very little computational effort. Another benefit of this approach is that plant pathogens can be detected at an early stage, or even at the beginning.

The paper [13] presents a state-of-the-art analysis of various approaches for detecting leaf disease using image processing techniques.

Table 1. Report on various algorithms used and its challenges in plant leaf disease detection

Citation	Algorithm used	Conclusion drawn
Ghaiwat et al. [15]	ANN, SVM, PNN, SELF ORG MAPS and fuzzy logic	In neural network it's difficult to understand structure of algorithm and to determine optimal parameters when training data is not linearly separable
Sanjay B. et al. [16]	Vision-based detection algorithm.	Adopting Neural networks technique to increase the recognition rate of classification process
Mrunalini R. et al. [17]	K-means clustering algorithm along with neural networks	Artificial neural network and fuzzy logic with other soft computing technique can increase the performance in crop diseases classification
Arivazhagan et al. [10]	SVM classifier	The training samples can be increased and shape feature and color feature along with the optimal features can be given as input condition of disease identification
Kulkarni et al. [18]	Gabor filter for feature extraction and ANN classifier for classification	Recognition rate can be increased using good machine vision systems
Bashir et al. [19]	Texture segmentation by co-occurrence matrix method and K-means clustering technique	Application of Bayes classifier, K-means clustering and principal component classifier can increase the accuracy in classifying various plant diseases
Naikwadi et al. [20]	The color co-occurrence texture analysis method was developed through the use of spatial gray-level dependence matrices	Better result of detection can be obtained with the large database and advance feature of color extraction
Chaudhary et al. [21]	Median filter is used for image smoothing and threshold can be calculated by applying Otsu method	Disease spot area can be computed for assessment of loss in agriculture crops. Disease can be classified by calculating dimensions of disease spot
Sujatha et al.[22]	Compared various ML (Support Vector Machine (SVM), Random Forest (RF), Stochastic Gradient Descent (SGD)) & DL (Inception-v3, VGG-16, VGG-19) algorithms to classify citrus diseases on leaves and fruits	DL performed better than ML algorithms

The latest methods of experiments are aimed at improving throughput and reducing subjectiveness caused by naked eye examination, which is used to identify and diagnose plant diseases. Barbedo et al. [14] conducted a study on various strategies for identifying, quantifying, and classifying plant diseases using visual imagery using digital image processing techniques. They focused primarily on plant pathology and pattern recognition.

Table 1 presents a brief report on various algorithms applied on plant leaf disease detection.

Insect and pest management in open-air and greenhouse agricultural contexts is another demanding task. The most common method of pest and disease control is to spray insecticides evenly across the cropping area. In terms of both money and the environment, this strategy is prohibitively expensive. Precision agricultural management also employs computer learning, deep learning, and image recognition. A method for recognizing and distinguishing healthy *Silybummarianum* plants from those affected by the smut fungus *Microbotyum silybum* during vegetative development is described in the literature [23]. The author in [24] offers a novel approach for parasite identification and automated thrips detection in a strawberry greenhouse setting for real-time monitoring utilizing image processing techniques based on a photograph. A technique for identifying and screening Bakanae disease in rice seedlings was reported by the researcher [25]. The researchers wanted to see if they could reliably identify the fungus *Fusariumfujikuroi* in two distinct rice varieties. The author proposed an automatic detection method for diseased plants to minimize manual inspection and enhance grain output while saving time. Wheat is one of the world's most frequently traded crops. Based on a hierarchical self-organizing classifier using hyperspectral reflectance imaging data, the authors in [26] created a novel method for identifying nitrogen-stressed, yellow-rust-infected, and healthy winter wheat canopies. The goal was to be able to detect these forms accurately so that fungicides and fertilizers could be applied more efficiently based on the demands of the plant. In [27], the author proposed a method that could automatically differentiate between water-stressed Septoria tritici-infected winter wheat canopies and healthy winter wheat canopies. The hybrid optical multisensor fusion was combined with the least squares (LS)-SVM classifier. Based on ANN models and spectral reflectance properties, the scientists proposed a technique to detect either yellow rust infested or stable wheat. Pesticides can be carefully targeted in the field after successful detection of ill or stable plants.

In [27], a real-time remote sensing technique for identifying yellow rust infected and healthy wheat was released. The method combines data fusion with hyper-spectral reflection and multi-spectral fluorescence imaging, as well as a self-organizing map (SOM) neural network. The goal of the study was to find a way to consistently detect winter wheat infected with yellow rust before symptoms appeared. Later, the authors [28] proposed a technique for identifying and distinguishing yellow rust-infected, nitrogen-stressed, and stable wheat plants of the cultivar “Madrigal " at the same time. A SOM neural network and hyperspectral reflectance imagery are utilized in this technique. The goal of the study was to determine if disease-induced plant stress and nutritional shortage could be distinguished reliably. Finally, in [29], the author proposed a CNN-based disease detection diagnosis technique based on basic leaf pictures that was precise enough to distinguish between stable and sick leaves in diverse plants.

4.2. Weed Identification

Weed identification and management is another significant problem in agriculture. Many farmers consider weeds to be the greatest severe threat to agricultural output. Because weeds are difficult to categorize and distinguish from crops, weed identification is critical for sustainable agriculture. Weed identification and discrimination would be achieved at a cheap cost, with no harmful environmental or side effects, if machine learning and deep learning algorithms were combined with sensors. Crop identification based on machine learning might help with the development of weed-eradication equipment and robotics, decreasing the demand for pesticides.

Table 2. Report on various crops, Algorithms used and features considered

Author	Name of the Crop	Algorithms	Features Considered
23	Silybum marianum	Artificial Neural Networks (ANN)	leaf Images captured using NIR spectrometer
24	Strawberry	Support Vector Machine (SVM)	Color indices such as hue, saturation, and intensify; and a leaf region index dependent on the major diameter to minor diameter ratio.
25	Rice	Support Vector Machine (SVM)	Bakanae disease, rice seedlings extracted using Morphological and color traits
26	Wheat	Artificial Neural Networks (ANN)	Hyperspectral reflectance imaging data
27	Wheat	Least Squares-Support Vector Machine (LS-SVM)	Spectral reflectance and fluorescence features
28	Wheat	Multi Layer Perceptron (MLP)	Spectral reflectance features
29	Wheat	Self-Organising Map (SOM)	Hyper-spectral reflection and multispectral fluorescence imaging
30	Wheat	Self-Organising Map (SOM)	Hyperspectral reflectance images
31	Generalized approach tested on 25 various crops in total	convolutional neural network (CNN)	leaf images of healthy and diseased plants
32	Silybum marianum	Counter Propagation (CP)	leaf Images captured using NIR spectrometer
33	Maize	one-class Self-Organising Map (SOM) and Clustering	Spectral reflectance features from hyperspectral imaging
34	grassland cropping	Support Vector Regression (SVR)	Photos of grass and different varieties of weeds taken with a camera

In [32], the author proposed a novel technique for identifying *Silybum marianum*, a plant that is difficult to remove and causes significant crop production loss, based on counter propagation (CP)-ANN and multispectral images collected by unmanned aircraft systems. The scientists [33] then used machine learning techniques and hyperspectral imagery to create a novel approach for detecting crop and weed species. The scientists devised a new method for identifying crop and weed species based on machine learning techniques and hyperspectral photography. The authors created an adaptive learning system to distinguish Maize (Zea mays) from weeds such as *Ranunculus repens, Cirsium arvense, Sinapis arvensis, Stellaria media, Tarraxacum officinale, Poa annua, Polygonum persicaria, Urtica dioica, Oxalis europaea,* and *Medicago lupulina*. In a separate study [35], the authors developed an SVN-based weed detection method for grassland cropping.

Table 3. Crop, Algorithms used and percent accuracy achieved

Name of the Crop	Algorithms	Results	Metric used
Silybum marianum	Artificial Neural Networks (ANN)	95.16%	accuracy
Strawberry	Support Vector Machine (SVM)	2.25%	Mean Percentage Error (MPE)
Rice	Support Vector Machine (SVM)	87.90%	accuracy
Wheat	Artificial Neural Networks (ANN)	99.63%	accuracy
Wheat	Artificial Neural Networks (ANN)	99.83%	accuracy
Wheat	Artificial Neural Networks (ANN)	97.27%	accuracy
Wheat	Least Squares-Support Vector Machine (LS-SVM)	98.75%	accuracy
Wheat	Multi Layer Perceptron (MLP)	99.40%	accuracy
Wheat	Self-Organising Map (SOM)	99.40%	accuracy
Wheat	Self-Organising Map (SOM)	99.92%	accuracy
Generalized approach tested on 25 various crops in total	convolutional neural network (CNN)	99.53%	accuracy
Silybum marianum	Counter Propagation (CP)	98.87%	accuracy
Maize	one-class Self-Organising Map (SOM) and Clustering	98%	accuracy
grassland cropping	Support Vector Regression (SVR)	95.10%	accuracy

Next, Table 2 and 3 presents the report on crop and weed disease prediction along with algorithms used, metric applied and results.

CONCLUSION

It is extremely difficult to classify plant diseases using digital photographs. Much of the technological problems associated with plant disease classification seem to be addressed by machine learning, deep learning methods, and CNNs in particular. Farm management systems are turning into true artificial intelligence systems by using machine learning and deep learning techniques to sensor data, offering deeper suggestions and insights for possible decisions and operations with the ultimate goal of performance improvement. Machine learning algorithms and deep learning models are expected to become considerably more widespread in the future, enabling the development of integrated and helpful solutions. All of the techniques presently focus on specific approaches and tactics and are poorly connected to the decision-making process, as proven in other application areas. In accordance with so-called knowledge-based agriculture, this combination of automated data collection, data analysis, intelligent learning implementation, and decision-making or assistance will have practical implications for bio-product production standards and productivity.

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Chapter 5

PLANT DISEASE DETECTION USING IMAGE SENSORS: A STEP TOWARDS PRECISION AGRICULTURE

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ABSTRACT

Plant diseases pose a major threat to crop production worldwide. In the past, human beings have encountered some severe epiphytotics which disrupted the food supply and led to famines. The major cause behind the development of an epiphytotic is our inability to identify a plant disease at an adequately early stage before it affects a larger plant population. In this regard, a quick, reliable and early detection may be useful. For the early detection of plant diseases, recently optical sensing techniques have been employed for the real-time monitoring and identification of diseases and finding remedies for them. Different imaging techniques employing different kinds of image sensors like RGB sensors, IR/thermal sensors, hyperspectral sensors and multispectral sensors *etc*. along with computer vision approaches can be effectively utilized for the quick identification and classification of plant diseases. The first step in this regard is image acquisition, which is followed by segmentation, feature extraction and classification. These applications of image sensing in plant pathology along with an Artificial Intelligence (AI) based decision support system could be a way forward in achieving precision agriculture with enhanced protection against plant diseases. The present chapter, therefore, highlights the prospects and challenges in the field of plant disease detection using various types of image sensors.

Keywords: hyperspectral imaging, thermal imaging, image segmentation, plant pathogen, precision agriculture

INTRODUCTION

The rapid increase of the global human population and a quick, corresponding decline in the area under cultivation had huge impacts on agricultural practices worldwide. Hence, there has been a recent gradual shift from traditional agricultural practices to precision agriculture. Out of these practices, plant protection practices are one of the most important ones [1]. With a change in consumer's behaviour and attitude towards processed foods, the availability of smart devices, internet connectivity and access to the latest technologies, a modern field of agriculture, which is known as 'precision agriculture' or 'smart farming' today, has rapidly grown. Early detection of any plant stress (due to either biotic or abiotic factors) has been a major challenge for sustainable agriculture and smart farming.

Among the various biotic and abiotic factors leading to plant stress, the plant diseases caused by a variety of plant pathogens (*viz*., viroids, virus, bacteria, fungi, nematodes *etc*.) pose a serious threat to global food security, and the timely identification of pathogens is very important from the perspective of disease management. Traditionally, disease monitoring has been practiced by plant pathologists keeping in view the visual estimation of disease spread and its severity. Visual assessment may not be very precise. Besides, it is laborious and expensive too [2]. Advances in techniques such as PCR and DNA sequencing subsequently followed by the bio-informatic support (for sequence comparisons) made it possible to devise the early detection systems for different plant pathogens [3-5].

The inability of the human eye to work beyond the visible range of the electromagnetic spectrum limits the visual assessment to a short region of the spectrum. Various optical sensors *viz*., RGB (red, green, and blue) wavebands, 3D-imaging, chlorophyll-fluorescence imaging, thermography, and multispectral (MSI) and hyperspectral imaging (HSI) have recently been used for the detection of plant diseases [6]. Except for RGB, these imaging technologies generate data that is beyond the usual visual range and opens doors for the newer range of possibilities in early detection of plant diseases, their forecasting as well as their management. The optical properties of a crop are measured within various regions of the electromagnetic spectrum, using different kinds of image sensors. Changes in leaf colour, shape, morphology, transpiration rate, and plant density can be detected in the early stages of infection [7-8], which enables a plant pathologist to go for a timely management decision regarding disease control. Further, these methods are non-invasive and non-destructive in nature [9], due to which the adoption of the methods in precision farming is advocated. Processing of the data from various image sensors requires computational analysis for assessing plant health. The development of sophisticated computational techniques and instruments has emerged as a new approach for real-time scanning and detection of disease symptoms in infected plants or plant parts [10].

Plants are frequently damaged by different plant pathogens. Due to this, the economic value of harvest is reduced. Therefore, any early, on-site pathogen detection system using a non-destructive method could have immense potential to devise appropriate disease management practices. Standard plant pathological methods (regular monitoring of signs and symptoms is the field, visual examination, both at macroscopic and microscopic levels of the diseased specimens in the laboratory) and molecular detection methods (supported by DNA sequencing and bioinformatics tools) are time tested, accurate and reliable; but early (even before human eye can detect) and real-time detection in a non-destructive way is difficult to achieve in the field using these conventional methods. Recent developments in the area of artificial intelligence (AI) have introduced machine vision-based, indirect methods for plant disease detection and classification [11]. A sub-set of Machine Learning (ML), known as Deep Learning (DL), has great potential in terms of increased accuracy and is gradually becoming the leading approach in many fields, including agriculture [12-14]. The Deep Learning approach was first introduced in the year 1943 and has been evolving continuously since then [15]. To detect and classify the signs and symptoms of plant diseases, many modified DL architectures have been implemented along with the support from several visualization techniques [16]. These methods utilize various algorithms such as linear regression, random forest, logistic regression, clustering, Gaussian models, decision trees (DT), Naïve Bayes (NB), K-nearest neighbors (KNN), and support vector machines (SVM), etc. Different types of deep neural networks (DNNs) and Convolutional neural networks (CNNs) have performed well in the classification of crops, fruit counting, prediction of yield and other vision-related tasks too in addition to the detection of plant diseases [17-21]. Recent advances in the use of different types of image sensors and subsequent computer-vision support have paved the way for early plant disease detection and management, which could be as handy as a smartphone assisting plant disease detecion

[22, 23]. Prognosis of the plant diseases based on weather predictions and epidemiology of the pathogen can help in an accurate forecast of a plant disease and its impacts [24]. The thermal image sensors are capable of detecting even small changes in temperature and moisture levels, which can help in predicting disease development and pathogen reproduction [25]. Innovative technologies such as HSI and their analysis have shown tremendous potential in disease detection and revealing plant-pathogen interactions [26, 27]. Many plant diseases often produce patchy appearances in the crop fields. Several studies have shown that optical sensors can be used to map disease foci and calculate disease incidence on this basis [28, 29]. The application of imaging techniques such as RGB-based, thermal imaging, fluorescence imaging and HSI have solved various practical problems in the fields of biology, medicine and agriculture. Researchers throughout the world are developing various plant disease recognition models using image processing and soft computing. Further, the remotely sensed images by the sensors on the aircraft/satellites can also be used to monitor crop health on the basis of spectral, spatial and temporal changes. This area is now a well-developed discipline in its own and it is referred to as 'remote sensing.'

In the present chapter, we have discussed different types of image sensors and the progress made so far in their applications towards the efficient and early detection of plant diseases. We have also tried to highlight the prospects and challenges in plant disease detection by using different image sensors.

VARIOUS IMAGE SENSORS

Imaging is a technique of capturing, processing, storing and re-presenting a piece of visual information for the purpose of investigation, analysis, information or simply (tele-)casting; it has immense uses in precision agriculture. There are numerous applications of image processing in agriculture. Such applications could be more time saving and economical for farmers [30-31]. However, the most important step in imaging techniques before the downstream image processing is image acquisition by using an appropriate image sensor. Modern imaging techniques are digital in nature because it is easier to store, process and manipulate digital information than the analog one. Any image capturing equipment or a camera, in general, captures a band of light reflected from an object or a landscape (or scene). The optical component of the camera is used to adjust the focus (focal length) and span of the scene (aperture) to capture a plane of the image. The basic principle is to capture reflected light from a focal scene and optically transfer it to a light-sensitive grid of electronic pixels, called an image sensor. Image sensors come in a variety of pixel configurations ranging from 80 × 60 to 1280 × 1024 pixels or more (also called the resolution of the camera). Depending on the sensitivity of the image sensor to a particular spectrum of light (electromagnetic waves), there are different types of image sensors *viz*., thermal, RGB sensors, multispectral/hyperspectral sensors, *etc*. The image sensor is equipped with surrounding electronics or ROIC (Read-Out Integrated Circuit) that transform(s) a weak photocurrent from grid organized pixels to a final digital bit-map image.

RGB Image Sensors

Humans have biological visual sensors (i.e., eye) with three different sensitivities to approximate the colours in a scene. RGB image sensors are designed to explicitly capture red, green and blue colours from a visible spectrum of light reflected from a scene [32]. The mechanism involves capturing a focal scene to the RGB sensor array. The sensor array is made up of a grid of photodiodes organized into clusters. Each cluster has photodiodes coated with Red, Green, Blue and No (clear) filters. A typical 8 × 8 RGB array will have 16 red, green, blue and clear photodiodes each (Figure 1). A red filter coating allows only red incident light to fall on the photodiode and prevents any other spectrum of light. Thus, a red filtered photodiode produces a photocurrent corresponding to red light [33]. Similar photocurrents are produced by other photodiodes. Supporting electronics converts the composite current values to an equivalent frequency square wave that is processed and transported by a computer or an IoT device.

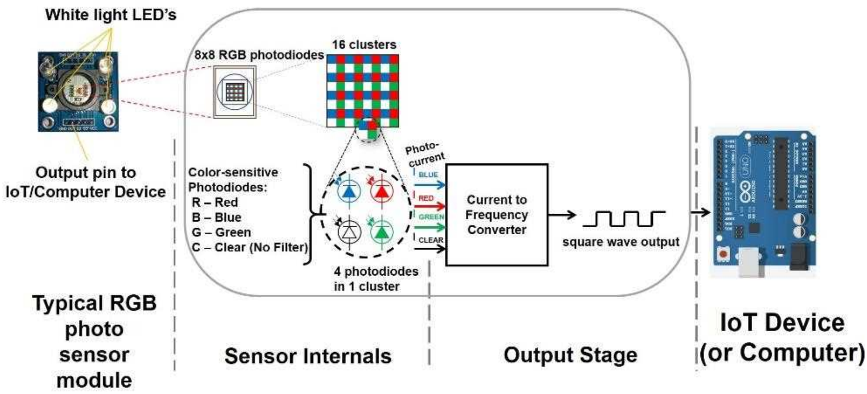

Figure 1. A typical RGB imaging mechanism

Table 1. RGB sensors used in early detection of plant disease

S.No.	Disease	Pathogen/causal agent	Plant host	Reference
1	Citrus Peel Diseases (canker, greasy spot, scab, melanose and insect damage)	Multiple diseases	Grapefruits (*Citrus* × *paradisi*)	[117]
2	Olive leaf spot disease	*Spilocaea oleaginea*	Olive (*Olea europaea*)	[118]
3	*Cercospora* leaf spot	*Cercospora beticola*	Sugar beet (*Beta vulgaris*)	[113]
4	Stripe (yellow) rust	*Puccinia striiformis* f. sp. *tritici*	Winter Wheat (*Triticum aestivum*)	[43]
5	Potato late blight	*Phytophthora infestans*	Potato (*Solanum tuberosum* L.)	[119]
6	Chlorosis	Iron deficiency	Soybean (*Glycine max*)	[49]
7	Tomato plant diseases	Multiple diseases	Tomato (*Solanum lycopersicum*)	[120]
8	Phymatotrichopsis root rot disease	*Phymatotrichopsis omnivora*	Alfalfa (*Medicago sativa*)	[45]
9	*Aphanomyces* root rot	*Aphanomyces euteiches*	Lentil (*Lens culinaris* Medik.)	[121]
10	Verticillium wilt	*Verticillium dahliae*	Olive (*Olea europaea*)	[47]

Table 2. IR sensors (thermography) used in early detection of plant disease

S.No.	Disease	Pathogen	Plant host	Reference
1	Tobacco mosaic Disease	*Tobacco mosaic virus* strain-TMV-U1	Tomato (*Solanum lycopersicum*)	[73]
2	Downy mildew disease of cucurbits	*Pseudoperonospora cubensis*	Cucumber (*Cucumis sativus*)	[59]
3	Apple scab	*Venturia inaequalis*	Apple leaves	[79]
4	Tomato mosaic disease	*Tobacco mosaic virus* (TMV)	Tomato (*Solanum lycopersicum*) leaves	[90]
5	Powdery mildew	*Erysiphe graminis* f. sp. *tritici*	Wheat (*Triticum aestivum* L.)	[84]
6	Powdery mildew	*Erysiphe graminis* f. sp. *tritici*	Wheat (*Triticum aestivum* L.)	[68]
7	Early and late leaf spot	*Mycosphaerella arachidis* and *Mycosphaerella berkeleyi*	Peanut (*Arachis hypogaea*)	[69]
8	Stripe rust (Yellow rust)	*Puccinia striiformis*	Wheat (*Triticum aestivum* L.)	[70]
9	Tea diseases	Multiple pathogens	Tea (*Camellia sinensis*)	[71]
10	Downy mildew disease of cucurbits	*Pseudoperonospora cubensis*	Cucumber (*Cucumis sativus*)	[111]

RGB-based imaging is replacing the human vision system to recognize any diseases and pests to assess the quality of different food articles (processed or fresh), weed and crop mapping, determination of secondary metabolite, non-invasive estimation of nutrient status (e.g., nitrogen content) and estimation of chlorophyll content in micro-propagated plants [34-38]. The RGB imaging method employs sensors that can utilize red (wavelength 550-750 nm), green (wavelength 500-549 nm), and blue (wavelength 400-499 nm) regions of the spectrum to produce image data [39]. These sensors usually allow the quantification of images by the three basic colour values (i.e., red, green and blue), resulting in integrated response over spectral bands. In this way, a broad array of colours is formed [40]. The optical property of plants depends upon the transmission of light through tissues, absorption of light by pigments, sugars and water, and reflection of light. The digital images produced by these sensors can be analyzed at the field/farm level also and they can be used for detecting the changes in plant tissues as well as other abnormalities [6, 41].

In the last decade, researchers used RGB indexes for assessing the losses caused by fungal pathogens and detecting the level of resistance to specific diseases (like yellow rust of Wheat) and also for the prediction of grain yield thereof [42-44]. The RGB sensors can be equally effective in the acquisition of aerial images (from aircraft/satellites) in a high resolution that can be effectively utilized for plant disease monitoring. Mattupalli and co-workers provided a framework on the supervised classification of RGB aerial imagery to evaluate the impact of a Phymatotrichopsis root rot disease in alfalfa [45]. RGB images can also be utilized for determining the concentration of metabolites synthesized by plant pathogens (like mycotoxins), which can have direct implications in the quality control of food stuffs, and thereby, in human health. RGB imaging analysis was also adopted for the determination of a toxin (deoxynivalenol) in the plants affected by *Fusarium graminearum*. It was shown that the RGB image analysis is relatively inexpensive, easy to use and a viable alternative to analyze the effect of pathogen on plant growth and microbial toxin contamination than conventional counterparts [46].

In olive plants, early effects of *Verticillium* wilt were detected by RGB indexes and the results showed significant differences between untreated and inoculated (treated) plants [47]. Goluguri and co-workers reviewed image classifiers and image deep learning classifiers used in the detection of rice diseases such as blast, sheath blight, brown spot, leaf smut and scald. RGB imaging techniques have also been significantly adopted to detect abiotic stress (or diseases due to abiotic factors) in plants [48]. Abiotic stress such as iron deficiency chlorosis in soybean plants leads to stunted growth, yellowing and interveinal chlorosis, which lead to the reduction of biomass. Bai and co-workers used RGB imaging and statistical learning models for the field-based scoring of soybean iron deficiency chlorosis [49]. Any abiotic or biotic stress condition may lead to variation in the morphological characteristics of the plant affected by it. These morphological and physiological traits can also be assessed using imaging techniques. Characteristics like leaf area, plant water consumption, and leaf water potential in drought stress affected grapevines were evaluated using such imaging techniques [50]. Recently, RGB sensors have also been utilized in phenotyping the root system of plants [51]. Water potential and chlorophyll content are important parameters in assessing plant health, both under biotic and abiotic stress conditions. RGB reflectance has been used for the prediction of the leaf water potential in potato [52]. The RGB based image analysis can also be successfully used to estimate the chlorophyll content of micro-propagated potato plants [37].

One type of image sensor, when used together with the other type, can be collectively used in a multi-model system. Recent research shows encouraging results on abiotic stress prediction in banana by multi-model data that utilizes RGB and thermal images [53].

Since both RGB and thermal systems in their experimental set-up have different resolutions, a model which trains on both types of images simultaneously may not have performed well; therefore, attempts have been made to train a unique model for each type of image separately. The investigation of the performance of remote sensing indices derived from thermal and red-green-blue (RGB) images combined with stepwise multiple linear regression (SMLR) and an integrated adaptive neuro-fuzzy inference system with a genetic algorithm (ANFIS-GA) for monitoring the fresh weight, dry weight, water content and total tuber yield in two potato varieties under three different evapotranspiration regimes (*viz.*, 100%, 75%, and 50%). The ANFIS-GA models gave the best predictions for the four plant traits in the calibration and testing stages. Therefore, the combined use of both RGB and thermal imaging indices with ANFIS-GA models could be successfully utilized for the management of the growth and production of potato crops under different irrigation regimes [54].

Further, many features of RGB images like color, gray levels, texture, dispersion, connectivity, and shape parameters can be effectively utilized for image classification and segmentation by using different pattern recognition algorithms and machine learning approaches [6]. Thereby, the detection and identification of plant diseases from RGB image sensors cab be more accurate and reliable. For this, the systematic selection of appropriate image features may lead to enhanced classification accuracies [55]. Digital image analysis is now also supported by some web resources like 'Quantitative plant' (https://www.quantitative-plant.org/) and databases [56].

Thermal Sensors

Temperature is one of the important physical parameters in many biological and industrial processes and the technique of thermography has revolutionized many disciplines of science, including plant science. Initially, infrared (IR) thermal imaging was developed for military purposes, but now the technique is well utilized in many fields like engineering, aerospace, medicine, agriculture, veterinary sciences *etc.* [57-59].

A thermal imaging sensor makes use of materials like InGaAs, which are more sensitive to shortwave infrared (wavelength ≈ 0.78 µm to 1.7 µm) and not the visible spectrum of light. Therefore, the thermal cameras capture pictures of heat, not of visible light like in RGB sensors. Everything we come across in our day-to-day life (even the ice) emits heat (IR waves) [60]. And the measurement of emitted radiations (IR) from an object is generally referred to as thermography. All the objects above -273.15°C emit in the infrared (IR) range of the electromagnetic spectrum. Thermal imaging converts the invisible radiation patterns of an object into analyzable, visible images. IR thermal imaging system consists of a thermal camera with an IR detector, a signal processing unit and a computer for image acquisition.

The InGaAs sensor array is primarily made up of a 2-D photodiode array. Each photodiode absorbs the incident IR radiation and transforms it into an electric current, which is read out and calibrated by the ROIC [61]. The Photodiode array has three layers *viz.*, indium phosphide (InP) substrate, InGaAs absorption layer, and an ultrathin InP cap (Figure 2). InP cap is an indium bump bonded to an ROIC, to which the camera pre-amplifier electronics gets connected. Further, the off-chip electronics manipulates collected electrical voltages to a bit-map to form a digital image [62]. Various models of thermal cameras are available now, which are working in different temperature ranges and a comprehensive listing of these cameras have been prepared by Al-doski and co-workers [63].

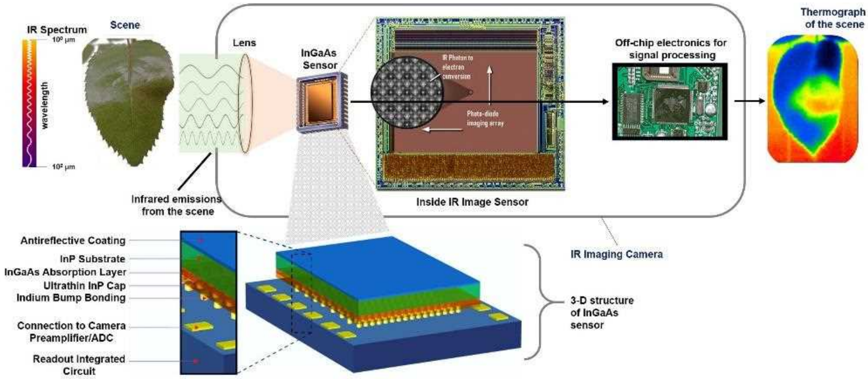

Figure 2. A typical IR (infra-red) image sensor used for thermography

The thermal imaging technique has been successfully utilized for the assessment of seed viability, estimation of water loss status in crops, scheduling irrigation, yield estimation, degerming maturity indices and in the determination of diseases in crop plants [64]. Two objects having different heat energies emit different IR wavelengths and are seen clearly in a thermal imager, regardless of light conditions. IR thermography is capable of assessing small differences in plant temperature, which could be present due to different kinds of biotic and abiotic plant stress factors [65-67]. Among biotic stress factors in plants, the diseases caused by different classes of pathogens (*viz*., Bacteria, fungi, viruses, phanerogamic parasites *etc*.) have been successfully detected in their early stages of infection by using thermography. Further, the technique has also been adopted to use for the detection of insect pests [63]. The thermal imaging sensor-based technique was also employed to detect the early incidence of the powdery mildew disease in wheat [68]. Thermal imaging technique and image spectroscopy has been used to detect the early stages of the peanut leaf spot disease on the basis of difference in spectral reflectance factors in healthy/disease leaves [69]. The spectral reflection was observed to be directly proportional to the disease incidence in peanut leaves. Healthy peanut leaves had decreased reflection, whereas unhealthy (diseased) peanut leaves had more reflection and it was observed that reflection further increases with the increase in disease incidence. In the case of thermal infrared range, the diseased peanut plants were observed to have relatively higher temperatures as compared to non-diseased (healthy) plants. Therefore, on the basis of the difference in temperature of affected/unaffected leaves, the early sensing of peanut leaf spot disease was made well before the appearance of the visible symptoms.

Thermal imaging technique was also used to detect the pre-symptomatic monitoring of wheat stripe rust [70]. Further, Yang and co-workers developed a fast infrared-based thermal image processing technique for the monitoring of tea diseases in tea orchards [71]. Both healthy and diseased images of tea plants were taken by using an infrared camera and accordingly, on the basis of thermal images, the tea canopy was classified. Further, a computer-based vision algorithm was developed to detect tea diseases by using thermal image processing technique. Moreover, in sweet potato (*Ipomoea batatas* L.), the co-infection of both *Sweet potato feathery mottle virus* (SPFMV) and *Sweet potato chlorotic stunt virus* (SPCSV) results in a severe viral disease [72]. IR thermography can also be used in different spatial and temporal scales with wide applications in plant sciences, especially in plant pathology. Plant pathogen infection results in the alternation of physiological functions in plants, such as a change in transpiration, photosynthesis, stomatal conductance, resistance responses and cell death [73, 74]. Thermography has been used to detect a variety of fungal pathogens, such as *Gaeumannemyces graminis* var. *tritici* and *Puccinia striformis* in wheat, downy mildew fungi in cucumber, *Plasmopara viticola* on grapes and apple scab *etc*. [59, 75-79]. Raza and co-workers combined the thermal and visible light imaging data and developed a machine learning system for the fast and accurate detection of powdery mildew fungus *Oidium neolycopersici* infecting tomato plants [80]. It was also utilized to observe the changes in metabolism after infection with *Rosellinia necatrix* in avocado and *Alternaria* in oilseed rape [81, 82]. Further, the infestation of insect pests may also be detected using thermal (IR) sensors. In addition to these reports, pests infecting palm trees were also detected by thermal imaging [83]. In another experiment, wheat plants grown under greenhouse conditions infected with *Erysiphe graminis*, the early disease incidence (pre-symptomatic) of powdery mildew disease was successfully monitored within ten days after sowing, employing thermal imaging technique [84].

Infection in kiwi fruit caused by *Pseudomonas syringae pv. actinidiae* was assessed by infrared thermography and the images revealed that the affected plants were warmer compared to healthy ones; and further, it was established that the pathogens infect the outer canes more than the central part of the canopy [85]. Similarly, the technique was also used for the evaluation of bacterial *Xanthomonas oryzae* and *Xylella fastidiosa* [86, 87]. The rate of transpiration from leaves affects the leaf temperature that may be easily detected by thermography [88]. The temporal post-infiltration changes in the thermal behaviour of two different concentrations of *Dickeya dadantii* suspentions were recorded by Pérez and co-workers in relation to plant transpiration in *Nicotiana benthamiana* [89].

Xu and co-workers applied the digital infrared thermal imaging technology along with the microscopic observations to investigate the early detection of tobacco mosaic virus strain-TMV-U1 infected/non-infected tomato leaves [73]. The discrimination between the temperature of TMV-U1 affected tomato leaves and the temperature of healthy tomato leaves was detected with the help of digital infrared thermal imaging.

The infection by a water mould (*Pseudoperonospora cubensis*) caused changes in transpiration rate due to the downy mildew disease in cucumbers [59]. The transpiration rate affected the leaf temperature, and therefore, the maximum temperature difference within the leaf was altered. This change in the leaf temperature was monitored through digital infrared thermography and it could indirectly visualize the incidence of the downy mildew disease in cucumbers. In another study by Oerke and co-workers, a localized decline in the temperature of apple leaves infected by *Venturia inaequalis* was observed resulting in an increase in the maximum temperature difference of the apple leaves [79]. It was further reported that the infrared thermal imaging technique may be helpful in disease screening/monitoring or disease quantification in precision agriculture. Early monitoring of tomato mosaic disease by using infrared thermal imaging technique has been reported in tomatoes [90].

IR thermal imaging has been used for the rapid detection of viral diseases of plants [20, 91]. The application of thermography in the detection of plant viruses is well documented for the pre-symptomatic visualization of plant-virus interactions [92]. Thermography can be utilized as an early reporter of an ongoing compatible plant-pathogen interaction [93]. The combination of more than one imaging technique, like the combination with thermal imaging with chlorophyll fluorescence imaging (Chl-FI) has been used to monitor the early changes in a host plant's physiology upon pathogen attack by estimating transpiration and photosynthetic efficiency respectively. Nowadays, Chl-FI is commonly used for phenotyping of plant responses alone and in combination with other image sensors to various biotic stresses and has been extensively reviewed elsewhere [94].

The pre-symptomatic detection of tobacco mosaic virus (TMV) disease in tobacco plants through chlorophyll fluorescence imaging (Chl-FI) technique and thermography was reported by Chaerle and co-workers [95]. Besides this, the early sensing of *Cercospora* leaf spot disease in the commercially important agricultural crop, *Beta vulgaris* (sugar beet) was also detected by employing both Chl-FI and thermography imaging techniques. Such imaging systems have also been robotized [93]. Further, this Chl-FI and thermal imaging platform was used for phenotyping viral infection in sweet potatoes [72]. Similar to Chl-FI, blue-green fluorescence has also been utilized along with thermography for the early detection of plant diseases/disorders. Thermography along with the blue-green fluorescence was used to detect pre-symptomatic infection caused by *Orobanche cumana* (root parasitic phanerogamic parasite) in sunflowers [96].

Hyperspectral and Multispectral Image Sensors

Imaging sensors are generally categorized on the basis of spectral resolution (i.e., the width of measurable wavebands), spatial scale and on the type of detector (imaging or non-imaging). Multi-spectral imagers capture spectral information of objects/scenes in relatively several broad wavebands. A typical multispectral camera can provide image data in R, G, B, near-infra (NIR) and even UV wavebands. Multispectral camera systems deploy a composite hybrid set of spectral filters and image sensors to capture multiple images over multiple bands of the electromagnetic spectrum [33]. On the other hand, a hyperspectral camera spans over an even wider and large number of spectral wavebands. A hyperspectral image data is usually organized as huge matrices with spatial x- and y- axes and spectral waveband information in the z-axis [6]. Further, the multispectral image (MSI) sensors can quantify the reflectance of the scene (plant tissue in this case) in only a few broad bands that may not necessarily contiguous but discrete, whereas the hyperspectral image sensors (HSI) can go for a somewhat continuous (in narrow contiguous bands) measurement of the spectrum, from the scene. Therefore, HSI processes a higher amount of information than MSI and handle a large amount of data at a particular time frame and requires higher computing configurations of the associated system to process the data to interpret results [97]. The detailed differences in the MSI and HIS are diagrammatically presented in Figure 4.

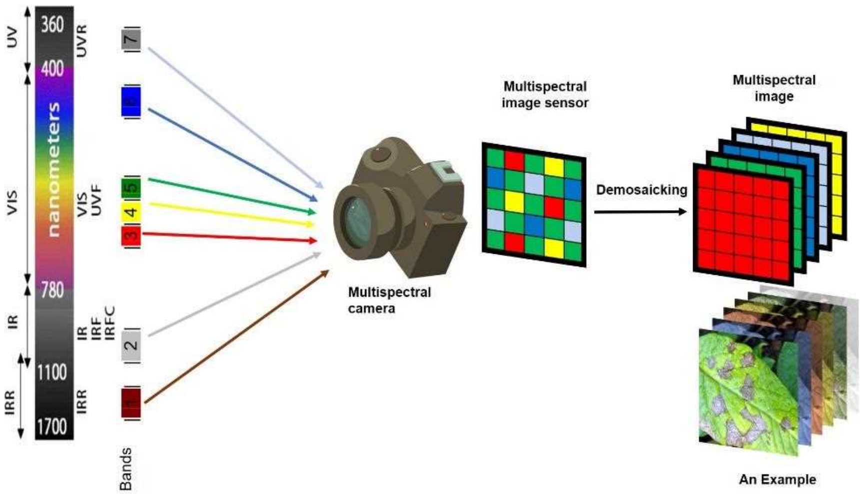

Figure 3. A typical multispectral image sensor system

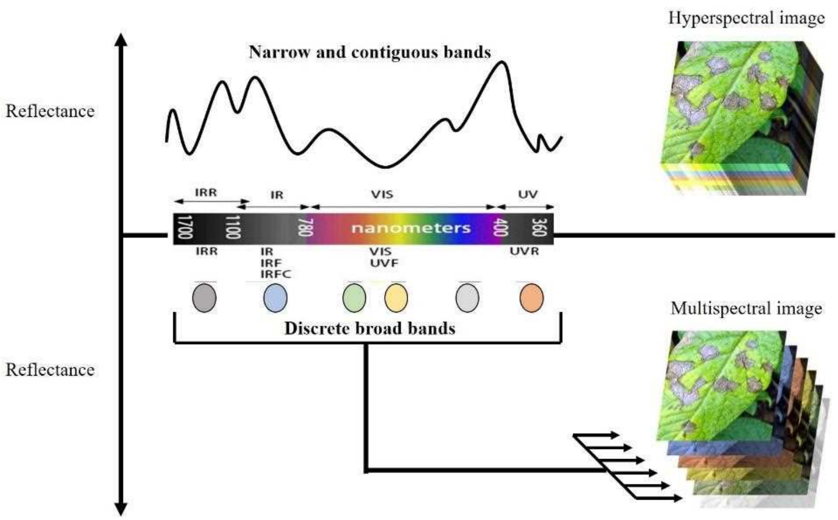

Figure 4. Difference in the mechanism of action in a typical hyperspectral and multispectral image sensor system.

Hyperspectral sensors are highly sensitive, which provide data that covers a spectral range of 350 to 2500 nm with a narrow spectral resolution below 1 nm [98]. HSI equipment consists of a hyperspectral sensor, a light source, and a control unit for taking and storing hyperspectral images. These components can be handheld or may be loaded on drones, robots, aeroplanes, tractors, and satellites, etc. Data is received from HSI in the form of a data cube that provides spatial information in a 2D image [99].

Table 3. Hyperspectral image sensors used in early detection of plant disease

S. No.	Disease	Pathogen	Plant host	Reference
1	Dark leaf and pod spot	*Alternaria* Spp.	*Brassica napus* (oilseed rape)	[82]
2	Tobacco mosaic	Tobacco mosaic virus	*Nicotiana tabacum* (tobacco)	[122]
3	Powdery mildew	*Erysiphe necator*	*Vitis vinifera (wine grapes)*	[123]
4	Leaf rust	*Puccinia triticina*	*Triticum* Spp. (wheat)	[124]
5	Powdery mildew	*Blumeria graminis*	*Hordeum vulgare* (barley)	[125]
6	Charcoal rot	*Macrophomina phaseolina*	*Glycine max* (soybean)	[126]
7	Cercospora leaf spot	*Cercospora beticola*	*Beta vulgaris* (sugar beet)	[127]
8	Downy mildew	*Plasmopara viticola*	*Vitis vinifera (wine grapes)*	[128]
9	Gummy stem blight	*Mycosphaerella melonis*	*Cucumis sativus (cucumber)*	[129]
10	Powdery mildew	*Leveillula Taurica*	*Capsicum annuum (bell pepper)*	[130]
11	Chlorosis and blotching	*Tomato spotted wilt virus*	*Capsicum annuum (bell pepper)*	[130]
12	Pear black spot disease	*Alternaria alternata*	*Pyrus communis* (pear)	[131]
13	Fruit decay	*Penicillium digitatum*	*Citrus spp.*	[132]
14	Bull's eye rot	*Pezicula malicorticis*	*Malus domestica (apple)*	[133]
15	Grapevine trunk disease	*Pezizomycotina* Spp.	*Vitis vinifera (wine grapes)*	[109]
16	Black sigatoka	*Mycosphaerella fijiensis*	*Musa* Spp. (banana)	[135]
17	Sheath blight	*Rhizoctonia solani*	*Oryza sativa* (rice)	[134]
18	Fusarium head blight	*Fusarium* Spp.	*Triticum spp.* (wheat)	[136]
19	Powdery mildew	*Blumeria graminis*	*Triticum* Spp. (wheat)	[137]

The optical properties of a plant are characterized by the light transmitted, absorbed and reflected by leaves. Plant water content can also be estimated using short-wave infrared (SWIR; 1000 to 2500 nm wavelength) imaging [100].

Table 4. Multispectral image sensors used in early detection of plant disease

S. No.	Disease	Pathogen	Plant host	Reference
1	Soybean Rust	*Phakopsora pachyrhizi*	Soybean (*Glycine max*)	[138]
2	Cucumber diseases	*Sphaerotheca fuliginea, Corynespora cassiicola, Pseudoperonospora cubensis, Trichothecium roseum* and *Cladosporium cucumerinum*	Cucumber (*Cucumis sativus*)	[139]
3	Aflatoxin-contamination	Filamentous fungi	Hazelnuts and ground red chili pepper flakes	[104]
4	Spinach fungal Seed diseases	*Verticillium* spp., *Fusarium* spp., *Stemphylium botryosum, Cladosporium* spp. and *Alternaria alternata*	Spinach (*Spinacia oleracea* L.)	[103]
5	Tomato spot wilt disease	*Tomato spotted wilt virus*	Peanut (*Arachis hypogaea*)	[140]
6	Mosaic and brown streak disease	*Bemisia tabaci* (whitefly) Insect vector	Cassava (*Manihot esculenta*)	[106]
7	*Barley's powdery mildew*	*Blumeria graminis f.sp. hordei*	Barley (*Hordeum vulgare* cv. Ingrid wild type)	[105]
8	Citrus greening	*Candidatus liberibacter*	Citrus fruits	[141]
9	Leaf spot in oilseed rape	*Pyrenopeziza brassicae*	Winter oilseed rape (*Brassica napus* L.)	[107]
10	Potato defects	Multiple diseases	Potato (*Solanum tuberosum* L.)	[108]

Spectral changes in the diseased plants may be linked to histological and biochemical analysis, using recently developed applications such as PROSPECT Model that uses the reflected and transmitted light to assess leaf compounds. Handling and processing the obtained data is a complex and laborious task in HIS [101]. Machine learning methods are proving to be very useful in analyzing hundreds of bands and are being established for monitoring plant diseases in laboratories, greenhouses as well as in fields [102].

Multispectral imaging with spectral bands of the wavelengths ranging from 395-970 nm has been used to test the seed health of *Spinacia oleracea* L. [103]. To differentiate aflatoxin-contaminated and the non-contaminated hazelnuts as well as the contaminated ground red chili pepper flakes, multispectral imaging have been successfully utilized [104]. The classification of fungal contaminated/uncontaminated hazelnut kernels through two-dimensional local discriminant-based algorithm showed an accuracy of 95.6% in testing aflatoxin contamination in hazelnuts. The multispectral imaging technique along with high-throughput enzyme activity signature profiling have also been employed to screen the resistance of barley against powdery mildew disease [105]. The narrow-banded light emitting diodes (LEDs) have been successfully used to automatically acquire the multispectral images with spatial resolution (five megapixels) at ten spectral (wavelength) bands i.e., 365, 460, 525, 570, 645, 670, 700, 780, 890, and 970 nm. Afterwards, multispectral imaging resulted in effective screening and diagnosis of powdery mildew of barley to identify disease resistant plants. A handheld and low-cost multispectral imaging sensor was developed for in-field detection and classification of insect vector (whitefly) of the mosaic and brown streak disease in cassava plants [106]. The multispectral imaging along with data-processing approaches could identify and discriminate the whitefly (i.e., *Bemisia tabaci*, a destructive crop pest of cassava and viral vector of the diseases) from other cryptic species.

In another study, multispectral imaging techniques were used to detect early symptoms of the leaf spot disease caused by *Pyrenopeziza brassicae* in Winter oilseed rape (*Brassica napus*) by Veys and co-workers [107]. The investigation employed the machine learning technique in the form of novelty detection and feature selection to facilitate the classification of targeted reflectance values. Further, a low-cost active multispectral imaging system was developed to detect the leaf spot disease by utilizing spectral information at very high accuracy levels to analyze the plant pathogen interactions. The potato defects were classified and detected by utilizing the single-shot method-based multispectral imaging system [108]. Total 25 spectral images (409 × 216 pixels spatial resolution) from a specified spectral band (between 676 and 952 nm) were taken for each potato and total 417 potato samples (with/without defect regions) were used in the study. Thereafter, the image contrast was improved (between with/without defect regions) with the help of the band math method, followed by the segmentation of defected regions. In the segmented regions, spectral and textural features were calculated and they were then used for the classification. This study concluded that single shot method-based multispectral imaging techniques could be successfully employed for the online detection of potato defects and their classification. Both hyper-spectral and multispectral imaging methods were used to evaluate their efficiency in diagnosing foliar symptoms of the grapevine trunk disease (Esca) in vineyards [109]. The study revealed that both airborne multispectral imaging and ground-based hyperspectral imaging techniques were successful in the in-field detection of foliar symptoms of Esca in vineyards over three successive years.

COMBINATION OF DIFFERENT IMAGING METHODS

More than one imaging method can be used together for the detection of plant diseases in a more precise manner than a single method. Some of such examples are listed in Table 5. For instance, thermal and fluorescence imaging methods have been employed for the early monitoring of various diseases in different plant species. It has been found that remote sensing in combination with the multispectral and thermal imaging techniques may prove more beneficial for precision agriculture [110].

Table 5. Collective use of multiple imaging sensors in plant pathology

S.No.	Disease	Pathogen/ causal agent	Plant host	Imaging methods	Reference
1	Tobacco mosaic disease	*Tobacco Mosaic Virus* (TMV)	Tobacco (*Nicotiana tabacum*)	Chlorophyll fluorescence imaging (Chl-FI) and thermography	[95]
2	*Cercospora* leaf spot	*Cercospora beticola*	Sugar beet (*Beta vulgaris*)	Chl-FI and thermography	[95]
3	Huanglongbing or citrus greening	*Candidatus liberibacter*	Citrus fruits (Valencia oranges)	RGB, Near Infrared (NIR) and Thermography	[110]
4	White root rot	*Rosellinia necatrix*	Avocado (*Persea americana* Mill) plants	Blue-green fluorescence, Chl-FI and thermography	[81]
5	Dark leaf and pod spot	*Alternaria* Spp.	*Brassica napus* (Oilseed Rape)	Hyperspectral imaging (HSI) and thermography	[82]
6	Broomrape disease	*Orobanche cumana* (root parasitic phanerogamic parasite)	Sunflower (*Helianthus annuus* L.)	Blue-green fluorescence and thermography	[96]
7	Powdery mildew	*Oidium neolycopersici*	Tomato	RGB and thermal sensor	[80]
8	Rice sheath blight	*Rhizoctonia solani*	Rice (*Oryza sativa* L.)	High-resolution RGB color and multispectral imaging	[143]
9	Viral Chlorosis and Mottling (Leaf deformation, yellowing, mosaic symptoms, dwarfing, vein clearing and stunting	*Sweet potato feathery mottle virus* (SPFMV) and *Sweet potato chlorotic stunt virus* (SPCSV)	Sweet potato (*Ipomoea batatas* L.),	Chl-FI and thermography	[72]

S.No.	Disease	Pathogen/ causal agent	Plant host	Imaging methods	Reference
10	Grapevine trunk disease (Esca)	Esca complex along with *Botryosphaeria* dieback and *Eutypa* dieback	Grapevine (*Vitis vinifera* L. cv. Phoenix)	Hyper-spectral and multispectral imaging	[109]
11	Abiotic stress disorder	Different water/fertilizer regimes	*Musa* Spp. (Banana)	RGB and thermal sensor	[53]
12	*Fusarium* head blight	*Fusarium graminearum* species complex	Durum wheat (*Triticum turgidum* cv. Marco Aurelio)	RGB, Thermal Imaging and Gene Expression Analysis	[142]
13	*Botrytis* infection	*Botrytis cinerea*	Arabidopsis (*Arabidopsis thaliana*) leaves	RGB and Chl-Fl imaging	[144]
14	Downy mildew	*Plasmopara viticola*	Grapevine (*Vitis vinifera*)	Chl-Fl and multispectral imaging	[145]

In an experiment to differentiate between healthy and diseased leaves of orange trees, the spectral reflectance values were analysed and it was possible to monitor the incidence/severity of citrus greening (Huanglongbing) disease using visible-near infrared and thermal imaging techniques [110]. It was concluded that the citrus greening disease affected plants had shown higher reflection in visible region of the spectrum as compared to the near-infrared region. The spectral reflectance was more in diseased orange trees as compared to non-diseased (healthy) trees. The highest separability was recorded at 560 nm and 710 nm wavelength in the visible-near infrared spectral regions. Further, it was suggested that simultaneous application of both visible-near infrared and thermal imaging techniques may be employed for automated, remote sensing-based plant disease detection methods for recurrent monitoring of disease severity in the citrus orchards.

The blue-green fluorescence, Chl-FI and thermography imaging techniques were used in the early detection of *Rosellinia necatrix* induced metabolic changes in the aerial parts (leaves) of avocado plants. These were caused due to the white root rot disease [81]. In another study by Baranowski and co-workers, both thermal and HSI techniques were used to detect the *Alternaria* induced disease in *Brassica napus* (oilseed rape) [82]. Both Chl-FI and IR thermal Imaging techniques were used to detect the virus distribution and accumulation in sweet potatoes. Recently for early detection of *Pseudoperonospora cubensis* causing downy mildew of cucumbers, two simultaneous imaging techniques *viz.*, thermal imaging and Fourier transform infrared spectroscopy were utilized [111]. Besides this, a comprehensive report by Sethy and co-workers also signifies the relevance of various image processing diagnostic tools and techniques for the detection of rice diseases [112].

FUTURE PROSPECTS

The age-old method for the detection of plant health was the careful observation of plant's morphology. But the human eye was capable of making observations in the visible range of the electromagnetic spectrum only. With the evolution of different types of image acquisition sensors with the enhanced computing abilities (supported by computers), humans were able to explore the regions beyond the visible range of the electromagnetic spectrum using IR sensors, multispectral sensors and hyperspectral sensors. These techniques have now evolved sufficiently enough to be capable of detecting plant diseases [6] well in advance before the human eye can observe. Sethy and co-workers, in a state-of-art review, discussed image acquisition, recent developments of image pre-processing, segmentation, feature extraction, feature selection and classification techniques [112]. Further, they suggested a common acceptable framework for paddy. They also discussed how the quality of images, number of training images and feature selection could directly affect the performance. Classifiers like support vector machines (SVM) can be effectively utilized for pixel-wise disease classification and quantification of images [113].

Digital imaging and aerial mapping combined with technologies like image processing, wireless sensor networks (WSNs), Internet of Things (IoT) and Artificial Intelligence (AI) have the potential to dramatically change the way we do agriculture today [114]. This technological merger has already been sprouted to offer smart agriculture with services like automated monitoring of the plant environment including soil, water, nutrition, diseases, pests, irrigation, fertilization, yield condition, greenhouse monitoring, *etc.*, if different sensor nodes are communicating over the internet [115]. There is a high possibility of the use of cloud-based solutions to collect the field information from wireless sensors, process with the help of the latest technologies like data analytics and AI in smart agriculture [116] to offer a safer environment, a healthier economy, the satisfied farmer and better nourishment and availability of affordable food for all. With these technologies, we are quite close to real-time disease monitoring, identification and classification of plant diseases. Various image features can be effectively utilized for image classification and segmentation by using different pattern recognition algorithms and machine learning approaches [6]. AI based decision support system could be a way forward in achieving precision agriculture with enhanced protection against plant diseases by the early recommendation of the plant protection interventions like spraying a fungicide. With the increased use of smartphones by the farming community, a mobile-friendly application (App) could be a handy tool for ultimate stakeholders, farmers, at least for RGB images in the near future from a plant pathologist’s perspective.

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Chapter 6

RECENT TRENDS IN AGRICULTURE USING IOT, CHALLENGES AND OPPORTUNITIES

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ABSTRACT

Agriculture and its supply chain are two of the most important fields of study in which all industrialised nations must focus their efforts. Food security and availability continue to pique the world's interest in its worth, and people depend on it due to health concerns. This system promises to provide all players participating in the value chain of agricultural food with fair resources, particularly though they

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are not interconnected. This article demonstrates the potential of agricultural wireless sensors and the Internet of Things (IoT), as well as the challenges that are expected to arise when this technology is integrated with traditional farming techniques. IoT sensors and wireless sensor-related connectivity techniques used in farming applications are studied in depth.

Keywords: IoT, IoT based agriculture, IoT based Sensor and Applications

INTRODUCTION

Agricultural commodity monitoring framework focused on Blockchain and IoT to manage the entire agricultural product lifetime process, which will significantly increase customer confidence in food and enhance the functioning of brand safety. In two different ways, an optimized solution to these issues is proposed, with the aim of using blockchain to encrypt the data of organizations involved in the agricultural food supply chain. [1-5]. Secondly, IoT technology is applied to the blockchain so that it is possible to track the entire commodity lifecycle to prevent the possibility of bad food safety and expiry. Analysis studies have shown that IoT networks offer efficient solutions to a range of agricultural problems and, in our case, blockchain would open a new corridor for the supply chain of agricultural foods in partnership with IoT, where all stakeholders (farmer, producer, seller, retailer and consumer) will allow straightforward transactions and build a trustworthy ecosystem for the field [6-10].

The sensors available for agricultural applications are listed, including soil preparation, crop condition, irrigation, and insect and pest detection. It demonstrates how this technology may help farmers throughout the agricultural cycle, from planting through harvesting, packaging, and transportation. This research also discusses the potential of unmanned aerial vehicles for agricultural monitoring and other useful uses, such as agricultural yield optimization. Production monitoring is a technique for assessing several characteristics of agricultural yield, such as low grain mass, moisture content, and the amount of harvested grain. It is possible to correctly measure how well the crop has grown and what to do next by monitoring crop yield and humidity levels. Yield monitoring is well-known as an essential part of precision farming, not just during harvest but also prior, since yield quality monitoring is critical. The quality of the yield is determined by a number of variables, including proper pollination with high-quality pollen, which is particularly important when seed yields are projected to fluctuate due to changing weather circumstances. Buyers throughout the globe are becoming more particular about fruit quality as we deal with more open consumers; consequently, effective development depends on matching the proper quantity of fruit to the proper demand at the appropriate time. Greenhouse farming is the earliest kind of smart farming. Indoor crops are also less harmful to the environment since they are not confined to simply absorbing light during the day [11-16]. As a result, crops that could previously only be produced under certain circumstances or in certain parts of the globe are now produced wherever. This was the true beginning of sensors and communication systems serving a wide range of agricultural applications.

INTERNET OF THINGS

Human interaction with data processing, tracking and verification, IoT devices are introduced to the smart model. The Internet of Things (IoT) is a concept that describes the use of intelligently linked sensors and networks in computers and other physical objects to leverage data provided by embedded sensor actuators. The Internet of Things is a philosophy that allows for contact with artifacts present in the world. IoT is mainly being used in cultivation. To know the values of soil pH, soil moisture, temperature and humidity, many sensors are given. Smart agriculture and IoT incorporating robots are examples of emerging technologies. Both environmental factors have a significant impact on seed production. It provides temperature control and humidity in the field through the sensors in this article. One of the important steps in the advancement of technology is the Internet of Things. Using advanced computational tools, IoT is able to link the world's real and virtual stuff together. People to people, people to things, and stuff to stuff are three types of IoT networks. Bluetooth-enabled wearable gadgets that are often linked to the Internet. Smart homes are now an essential part of IoT consumers' Internet access, thanks to wireless networking and home routers.

M2M applications that are specifically exposed to cellular networks are in the third group of IoT devices. Climate, soil moisture, soil temperature, soil productivity, and soil PH value may all be measured using sensors as well as determining if the crop's planned development period is adequate, and cultivating locations that are very valuable for maximizing output potential while minimizing natural and human resource waste. And also, by using sensors to identify the animals that reach the rising fields, we can design sound systems and then maintain the protection of the farming areas. To acquire characteristics such as pH, conductivity, temperature, and turbidity by measuring water content using sensors. Ultrasonic sensors, infrared sensors, humidity sensors, temperature sensors, gas sensors, URD sensors, and DHT sensors are all utilized in combination with other device controls to gather data in order to safeguard agricultural lands.

AGRICULTURE BASED IOT

The primary field in which significant changes have to be made is agriculture. In this article, we evaluated some of the methods of crop prediction based on their precision using algorithms of machine learning and real-time monitoring using the IoT of soil properties. The algorithms are used to ensure the good quality and quantity of the crop for improved crop prediction based on the soil properties.

To increase the real time usage of sensors in agriculture, there is a need to further develop IoT with machine learning techniques. IoT software must be quick to use in order for farmers to take advantage of them. To interpret data collected by sensors in real time using the Machine Learning Algorithm, we need to create applications.

A room-based navigation system is a GPS or Global Positioning System. GPS provides real-time data and location information, allowing you to go anywhere in any weather. In order to enable farmers to improve yield, GPS helps to control land capital. It also aids in livestock management. It is simple to use GPS to make animal farming decisions that do not necessitate a large number of human capitals. In cell phone networks, GSM or Global Mobile Networking System is predominantly used and it is a wireless mobile network. As this GSM device is used for the wireless network, farmers can track water, vegetation, atmosphere, temperature, etc., and get the information from the internet using a smartphone application. This makes it really convenient to tighten defense in agricultural areas.

Around the same moment, IoT or the Internet of Things was already being seen in several areas along with the latest technologies. Smart home, environment, women's and children's care, transportation, smart energy, waste management, smart growth, smart nature, smart business method, smart school, smart society, and so on . All can use Internet of Things (IoT) technology for something, at any time and in any place. Growing the use of IoT phase by step, the world's tremendous facilities move towards modernization. Without the user's tremendous effort, anything can be generated quickly, time and cost effectively and safely. IoT apps have also improved when increasing internet use.

Higher Yields---→ Automation -----→ Food Crops------→ Quality Food-----→ Crops---→ Industry----→ Chemicals------→ Land------→Geographic Effects ------→ Sensors-------→ Soil monitoring

Agriculture is one of the most significant fields of economic activity in the country. But the key problem is the protection of the sector of agriculture. Through the advancement of technologies utilizing IoT for agriculture, production can be increased and these agricultural areas can be well covered. Famers can get reliable, accurate knowledge and details with the aid of IoT gadgets with the highest productivity and efficiency without the user's big effort. Then, using those data, farmers may make good decisions about cultivation. This information, thus, would not only assist persons, but also private and public agencies. And the key reality is that the planned performance will not be achieved before the IoT is fully finished or introduced.

Agriculture would definitely profit greatly from AI implementations, for sure. AI will be used to build autonomous systems that are integrated in computers that can run with greater precision and speed than humans and be sensitive like humans at the same time. Along with IoT and Sensor Technologies, AI will be a key enabler of precision farming. In the large-scale application of Climate Smart Agriculture, AI, in combination with remote sensing technologies, will play a vital role. Any AI method, such as Mobile-based Recommender Systems and Expert Systems, will dramatically enhance the rate of adoption of agricultural technology such as high yielding or disease-resistant varieties, aiding farmers in boosting their earnings. Millions of farmers in our nation will benefit from these AI tactics as they transition from location-based advisory services to customized and context-specific assistance. Robotics, sensors, drones, the Internet of Things, and AI-powered solar power present new potential for enterprises and entrepreneurs to supply farmers with innovative technology as a product at reasonable pricing. Another area where AI may assist us is precision farming, which is more accurate in terms of crop kinds, weather conditions, and where and how we should go to cultivate crops. It can also assist farmers utilize the space they have. In agriculture, AI's most significant contribution is to remove monotony and boredom from many agricultural tasks, enabling us to focus our time and attention on developing new and innovative AI solutions that go beyond human capabilities.

The Internet of Things has demonstrated its usefulness in every industry, and its strength and flexibility have progressed to the point that it can now be used by the average person. Smart living, e-health services, robotics, and smart education are just a few of the techniques designed to make our lives simpler and more pleasant. Phenotyping is a technique used in agricultural research to better understand the elements that affect growth and to examine crop development in a range of real-world situations (e.g., soil quality, environmental conditions, etc.). In order to grasp the primary components in most agricultural research, phenotyping is required (e.g., soil pH levels, nitrogen depletion rate). By gathering linked time series data from sensor networks, geographical data from image sensors, and human perceptions recorded by mobile smart phone apps, Internet of Things (IoT) technology may lower expenses and expand the size of such investigations. IoT equipment, for example, might be used to capture soil pH levels and nitrogen degradation rates as time series data and share it with interested academics and producers for further study.

According to the results, IoT applications commonly gather air temperature, ambient humidity, and a range of other sensor data, such as soil moisture and pH, with soil moisture and pH being the most relevant sensor data for measurement. Wi-Fi, followed by mobile phones, has the biggest demand for use in farming and agriculture. Other technologies with a limited interest in the food and agricultural industries include ZigBee, RFID, Raspberry Pi, WSN, Bluetooth, LoRa, and GPRS Agricultural sector employs IoT for robots at a much lower rate than other industries. This survey may help academics come up with new solutions to tackle problems in the contemporary agricultural age, as well as the agricultural and agricultural sectors make automation more competitive and profitable, resulting in a favorable outcome for enterprises.

Precision farming is a sort of farm management and resource utilisation that incorporates the IoT and information and communication technologies (ICTs) into the process (ICT). It collects real-time data on the state of farm components in order to safeguard the environment, assuring benefit and long-term viability. Smart Irrigation is a means of increasing irrigation efficiency and lowering water losses by using Internet of Things-based smart irrigation devices to save current water supplies. Drones are employed in a number of agricultural applications, such as monitoring field crops and animals and scanning big fields, while sensors on the ground capture a variety of data. Smart greenhouses enable crops to grow with the least amount of human involvement possible by automating activities based on changes sensed and taking corrective action to maintain the best possible growing circumstances via the use of constantly controlled climatic conditions.

SENSOR NETWORK BASED ON AGRICULTURE

A WSN is a set of nodes that combine the roles of acquisition, processing, and communication. When installed, in order to track and/or manage a phenomenon, the nodes communicate with each other autonomously to capture and relay data to a base station. In fields as varied as the defence, medicine, the climate and precision agriculture, the usage of WSN is now experiencing a great boom.

Sensor networks, as an essential part of the IoT, enable us to communicate with artifacts in the real world. We are concerned with the architecture of the sensor network in this project that allows agriculture to be linked to the IoT. The relation creates relations between agronomists and farmers and thus increases the production of agricultural products. It is a systematic method developed to achieve agricultural precision. The experiments found that with an upgrade over conventional approaches, the wireless sensor networks were feasible. Each machine generated huge amounts of data that could be examined to identify patterns and associations using Big Data analytics. In the case of irrigation, data on irrigation activities will be built into farm machinery control systems to increase crop yields and the usage of fertilizers.

Time patterns can be used based on reported findings to prepare potential farming strategies. These IoT solutions can boost the practices of farming and contribute to more efficiency and improved resource usage.

APPLICATIONS OF VARIOUS SECTORS

In agriculture, IoT has diverse uses. It can be viewed as the genesis of late modern agriculture. By many orders of magnitude, the land for cultivation may be rendered propitious. It can be achieved by gathering data and details on different variables, such as temperature, wind speed, humidity, rainfall, soil quality, and pest infestation. It is possible to accessories this data as a cornerstone for different farming techniques. It is possible to use educated judgments to develop both qualitative and quantitative methods. In addition, to reduce the numerous threats and squandering, and to reduce the work needed to supervise crops. Through doing so, farmers can track soil temperature and moisture content from far away and can answer the knowledge or data gained from IoT for accurate fertilization programmers. For one and all of us by many orders of magnitude, agriculture is critical. By the use of the new technologies, every farmer in the world has a desire for both qualitative and quantitative agriculture, blazing a sufficient road for the world to live with a lot of satisfaction with good health. One and all human beings are based on agriculture. It is the primary survival need. We also suggested a method for this reason in order to support productive farming in an efficient manner, which is the need for agriculture.

Agribusiness is one of the essential IoT applications. There is a broad demand for premium dietary goods to meet the requirements of the general public as the population grows. IoT is an invention that renders the horticulture field self-sufficient and therefore decreases the expense of setting up various farming procedures.

The usage of smart farming technologies lets farmers cope with the way to grow livestock and establish harvests, save insufficient resources such as power, achieve cost-effectiveness, adaptability, and so on. Many problems in the field of agriculture can be solved and can produce outcomes of high caliber and quantity through creative headways within the cost constraints. Climate control, Green House Automation, Field Protection and Livestock Monitoring and Management are the use cases in the agricultural sector.

Precision irrigation, livestock control, pest prevention, and smart greenhouse are applications of IoT in agriculture. Precision farming is a technique that uses farm management information technology to send the right stuff in the right place, perfect time in the right way. The aim of precision farming is to obtain increased yield through resource conservation. The key goal of precision farming is to achieve maximum cost-effectiveness, productivity and soil resource security. Wireless sensors are the most useful of all the smart farming equipment now on the market, and they are essential for obtaining crop status and other information.

Depending on application needs, it was utilized solo or in combination with nearly any component of modern agricultural instruments and heavy equipment. The primary kinds of sensors are discussed in the following sections based on their functioning technique, purpose, and benefits. By helping to improve plant production, fertilizer often plays a very important function in the area of agriculture. Farmers can monitor soil conditions from any location using IoT to manage soil condition more effectively and at a lower cost. The major purpose of this research is to discover whether modern technologies, such as the Internet of Things and robots, can be employed in agriculture to save water, fertilizer, and energy. This benefits both the development of countries' economies and the wealth of individuals. IoT will track and count all associated performance components using a mix of specialized hardware and software technologies, reducing waste, loss, and cost. Only use of technological gadgets would one be able to get the information required to make informed judgments.

Agriculture is being transformed by the Internet of Things, which is supporting farmers in solving numerous challenges. Innovative ways that increase crop quality, quantity, lifespan, and cost-effectiveness may solve these concerns. IoT benefits the farming industry by improving animal health through better food and environment, addressing labour scarcity, cost reduction through robotics, milk quality, and rising in certain animals during the breeding process by sensing the estrus cycle, as well as additional revenue streams from waste.

Water shortage is a severe problem nowadays, and it must be managed effectively. It is a key source of agricultural product, which helps to enhance the economy of the area. To successfully manage and irrigate agricultural fields, a new approach called as the Automated Smart Irrigation Decision Support System is being deployed. On a weekly basis, the irrigation is measured. As a consequence, soil parameters, climatic parameters, and weather forecasts are computed once a week. For obtaining the SIDSS, the ANFIS and PLSR machine learning approaches are recommended. Human specialists and other research scientists carried out and analyzed the implementation. The SIDSS is carried performed using a variety of sensors. One of them is a soil sensor that detects different crops and circumstances before being modelled with a GSM/GPRS modem to gather data from various places. Rainfall, temperature, required water depth, and other environmental data are sent into the system.

Nitrates are a well-known contaminant that may be found in meats, fruits, and even water. It's harmful because it can trigger methemoglobinemia if the incidence rises past the expected level, which is thought to be caused by a blood difference caused by ferric ions. It may cause a number of ailments in both people and plants, with a rise in nitrate levels being the major culprit. When the same amount of nitrate is added to ground water, it affects plant and vegetable development, which has an influence on agricultural production. A smart nitrate sensor was put to monitor the quantity of nitrate in surface and ground water in order to remedy this. To monitor soil moisture nitrate, the unit is fully equipped with relevant equipment such as a planar interdigital sensor, instrumentation, and electrochemical impedance spectroscopy. The instrument can calculate the amount of nitrate deliberations in both field and surface water in the range of 0.01–0.5 mg/Litre.

Rather than using the spectrophotometric approach, there are many other ways to detect nitrate-nitrogen in water. Water samples from the river, lake, and even groundwater are collected and analyzed for nitrate detection on a regular basis. Furthermore, the system is designed to be low-cost to manufacture. The allowable amount of nitrate-N in drinking water, according to the Security Body, is 10 mg/Litre [ni]. Prior research has shown good accuracy in a range of situations. However, under some circumstances, there is a temperature differential between fields. The temperature effect compensation is then needed, and a low-cost temperature-compensated sensor is used to calculate the nitrate amount. The sensing system is linked to an IoT-focused cloud service through Wi-Fi networking.

Big data is critical for dealing with meteorological datasets and soil type parameters, which may be thrown by agricultural specialists or utilized by a drone-like robot to sprinkle seeds according on the data acquired. Another significant point to consider is that research has shown that the kind of fertilizer required for a certain soil may be identified. Similarly, in order to preserve the plants in the future, the kind of chemical to employ throughout the field depending on the crop will be selected ahead of time. Such data, including soil condition, crop kind, and pesticide and fertilizer needs, may be organized into a dataset.

Table 1. Number of Papers Published in IoT Based Agriculture

Year	**Number of Papers Published**					
	IEEE	IET	ELSERVIER	SPRINGER	WILEY	ACM
2017	20	18	30	35	20	18
2018	22	20	22	34	10	12
2019	24	18	28	38	10	15
2020	26	22	22	40	20	16

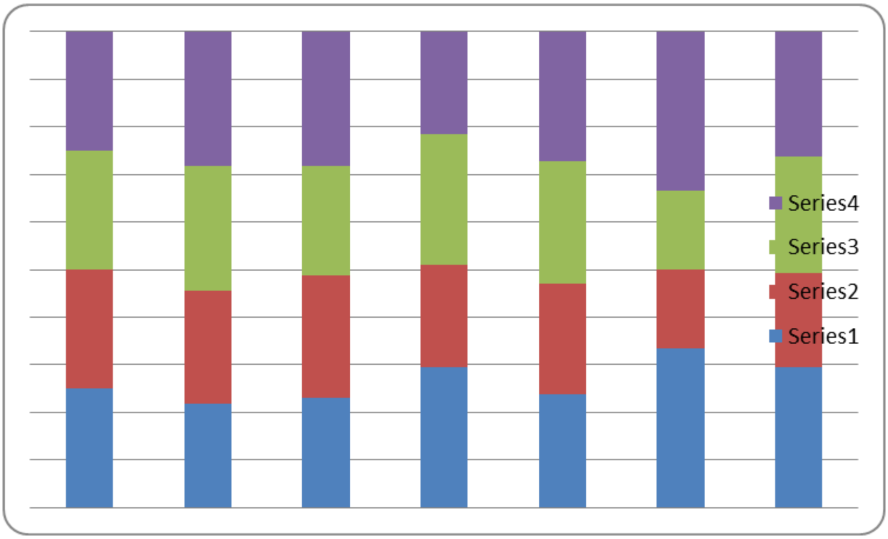

Figure.1. Comparison Chart for Publication in 2016-2020.

CONCLUSION

Irrigation in a register differs from location to location. It's difficult to estimate how much irrigation is required for agricultural reasons. As a consequence, determining when and where irrigation water is required is crucial, which may be accomplished utilizing ANFIS and PLSR approaches. There has been a lot of research on SSA recently, with terms like Precision Farming, Smart Irrigation, and Smart Greenhouse. To identify the interpretation of SSA provided in this article, this study begins by considering these definitions. Finally, in order to assure the agricultural environment's long-term survival as soon as feasible, the impact of IoT on the agro-ecological climate and the social economy should be addressed in the implementation of healthy agriculture.

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Chapter 7

EARLY DETECTION OF INFECTION/DISEASE IN AGRICULTURE

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ABSTRACT

Detectors are tiny devices used to minimize human effort and provide maximum yield.The previous work comprises sensing element that uses the fundamental measure, dampness knowledge in the dirt, and moistness existing in the encompassing atmosphere. The subsequent one has television equipment for sickness location. It uses picture preparation procedures. The third comprises robots and agrarian devices for the splashing of pesticides and composts. This detected data is then given to the simple to-advanced converting component through an Arduino and afterward to a Raspberry Pi. The information trades between the Raspberry Pi and the worker. These detectors consistently modify the data of the yield to the rancher. The user takes an essential activity by sending a reacting message. It conveys to the individual gadgets and the individual who worked gadget. The framework carries

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the harvest to ideal conditions. The proposal suggests a sampling methodology to detect the infection at an early stage by 10.4%.

Keywords: detectors, agriculture, precise-irrigation, sampling

INTRODUCTION

Detectors (Ambika 2020) (Akyildiz, et al. 2002) assemble many devices with different capabilities coming together to communicate with each other. These devices (A. Nagaraj 2021) use a common platform to talk to each other. Agriculture (Mat 2016) (Morais, Valente and Serôdio 2005) (Kim, et al. 2014) (Thakur, Kumar and Vijendra 2020) is the backbone of the country. Many measures taken provide a good yield. In recent times, pesticides are used in large quantities to overcome pest issues. The usage without using pesticides and producing good production is a focussing point. Detectors (AmbikaN 2020) (A. Nagaraj 2014) and machine learning (Williams and Hill 2005) algorithms provide answers to these problems.

WSN (Arampatzis, Lygeros, and Manesis 2005) (Baek, et al. 2009) can work in a scope of conditions. It benefits in price, size, energy, ability, and dispersed understanding, distinguish with connected ones. When a device cannot straightforwardly link with the server, the information conveys over various leaps. The organization could keep on working as devices are affected, conferred, or eliminated. Checking applications in medication, farming (Bhuiyan, Dougal and Ali 2010) (Ayday and Safak 2009), climate, military (Lee, et al. 2009), machine/building, and numerous fields. Models for detector networks change significantly throughout the nearly recent 50 years. It varies from simple 4-20 mA plans to the transport and organization geography of today. Transport designs (H. Lee 2014) decrease electrical circuits and needed compatibility transmission capability. Distant detectors further diminishing wiring needs, giving new freedoms to conveyed insight structures.

Agribusiness (Chaudhary, Nayse and Waghmare 2011) (Ojha, Misra and Raghuwanshi 2015) faces numerous difficulties such as environmental change, liquid deficiencies, work deficiencies. It is because of a maturing urbanized populace and enlarged ethical concern about problems. For instance, animal authorities said food handling and environmental consequence. It relies upon horticulture and liquid for strength, productivity, and feasible usage of our territory and liquid possession.

For the illness discovery of a harvest, the creators (Devi, et al. 2020) utilize two strategies. Picture Processing has four stages. It gets the required from various sources. Representation preprocessing improves quality. The undesirable commotion takes out from the image. Photo Segmentation partitions the picture into shares. Highlight Derivation takes out the undesirable portion. AI develops different calculations, takes the information sources lastly predicts the yield. The detectors take every one of the information boundaries and provide the Arduino UNO board, shipped off ThingSpeak worker. The woody plant assort calculation is the one that anticipates the yield by contrasting the ideal situation and the information situation. IoT-supported (Badhe, et al. 2018) brilliant liquid framework comprises a few parts. In little cultivating fields, natural conditions utilize detectors. The yield peruses an Arduino UNO associated with a Raspberry Pi. The code uses Python linguistic communication, and the information is put away in the SQLite data set. In huge cultivating zones, a remote detector network in which various detector hubs. The yield of the detectors associated with Zigbee for sending information to the door. A Web administration gathers the climate estimating information, and this data is given in these entries HTML, XML design. The Web administration reads the predefined way information utilizing API. The knowledge is in the MYSQL data set and considers in the forecast calculation. This calculation anticipates the dirt dampness and gives the meteorological forecast with the information. It uses the SVR model and incorporates a k-implies grouping calculation. The framework furnishes up to a level with a limit estimation of the dirt dampness. It halts after accomplishing that esteem.

Introduction is followed by literature survey in section two. Third section has explanation of proposed section. Fourth subdivision details the analysis. The contribution is concluded in segment five.

LITERATURE SURVEY

This section summarizes the work dedicated by divergent authors towards improving agriculture (Cambra, et al. 2017) (Dan, et al. 2015). For the illness discovery of a harvest, the creators (Devi, et al. 2020) utilize two strategies. Picture Processing has four stages. Picture obtaining is the way toward getting pictures from various sources. Representation preprocessing improves quality. The undesirable commotion takes out from the derived. Photo Segmentation partitions it into shares. Highlight Derivation takes out the undesirable portion, and just the needed or the sickness bit will be available. AI develops different calculations, takes the information sources lastly predicts the yield. The detectors take every one of the information boundaries and provide the Arduino UNO board, shipped off ThingSpeak worker. At that point, the choice woody plant assort calculation is the one that anticipates the yield by contrasting the ideal situation and the information situation. The IoT-supported brilliant liquid framework comprises a few parts. In little cultivating fields, natural conditions utilize detectors. The yield peruses an Arduino UNO associated with a Raspberry Pi. The code uses Python linguistic communication, and the information is put away in the SQLite data set. In huge cultivating zones, a remote detector network in which various detector hubs. The yield of the detectors associated with Zigbee for sending information to the door. A Web administration gathers the climate estimating information, and this data is given in these entries HTML, XML design. The Web administration reads the predefined way information utilizing API. The knowledge is in the MYSQL data set and considers in the forecast calculation. This calculation anticipates the dirt dampness and gives the meteorological forecast with the information. It uses the SVR model and incorporates a k-implies grouping calculation.The framework liquid is up to a level with a limit estimation of the dirt dampness. It halts after accomplishing that esteem.

The creators (Wark, et al. 2007) utilize this stage for both motionless and versatile devices.The static hubs depend on the Fleck-1,2 comprises an Atmega 128 microcontroller that runs at 8 MHz. A Nordic NRF903 radio handset with a piece pace of 76.8 Kbits each sec and an installed fundamental measure detector. These hubs are associated with grime dampness detectors or customized integral metallic compound compartments. Experiments have shown that these boards can create from 80 to 400 kilojoules of sun-oriented energy every month, a significant degree more than our present applications require. The versatile hub, the Fleck-2, is a Fleck-1 base increased by an assortment of movement detectors. It contains an installed triaxial electronic compass combined with three symmetrically mounted accelerometers just as a locally available GPS beneficiary. An 8-Mbit streak chip increased by a media card attachment can uphold up to 512 Mbytes of locally available capacity utilizing an MMC streak memory card. The dirt dampness hubs use industrially accessible ECH2O capacitor-supported detectors that encompass grime's volumetric liquid content. The organization consequently acquires interpretation, regularly at one-minute stretches, from every device and directs them back. Information is collected at the foundation to surrender a present dampness biography for the entire field.

The current work (Nandurkar, Thool, and Thool 2014) utilizes primary measure detectors for observing the dirt measure.LM-35DZ detectors give significant measures. The dirt fundamental measure is a factor with a deviation in the environment, earth science, flora, grime type, farming composition, and assorted elements. The grime measure is unwaveringly related to cycles. Some instances are harvest farming period, tailoring maturation, and season safety. The change of grime fundamental measure straightforwardly sways on grime supplement retention and grime dampness keep and game. The dirt measure presumes a particular part on a significant figure of the actual cycles of grime. The grime liquid and temperature motion is an exploration issue. The conceptualization of grime measure invariant. It has fundamental importance to initiation and formal exploration. The measured detector LM-35DZ has a yield electric potential that is corresponding to the measure. The measure component is 0.01 V. The LM35DZ doesn't need external accommodation or management and holds an exactness of 0.4-degree centigrade at room fundamental measure and ± 0.8-degree centigrade over a scope of 0-degree centigrade to +100 degree centigrade. Another significant trait of the LM-35DZ is that it pulls out 60 μA of current from its stockpile and has a low self-heating capability. The detector self-heating makes under 0.1-degree centigrade fundamental measure to go up in still air.

The LOFAR-agro project (Langendoen, Baggio, and Visser 2006) is the principal scope analysis in exactness farming in The Netherlands. This flyer undertaking involves the assurance of a root vegetable, harvest against fungus genus, contagious illnesses that spread effectively among plants, and obliterate a total gather inside an area. The turn of events and related assault on the yield relies upon the climatic conditions inside the field. Specifically, dampness and fundamental measure inside the yield shade are significant elements in improving the sickness. To screen these variables, they mean a root vegetable domain with remote detectors. The approximate checking of the microclimate can uncover the yield that is in danger of creating a fungus genus and permits the rancher to treat the field with fungicide. This exact treatment saves time, diminishes expenses. It restricts the use of climate with hostile substances instead of customary treatment-based data.

A sum of 150 indicators (Baggio 2005) sheets are the same as the Mica2 bits from Crossbow2 are introduced in a package for observing the harvest.The TNOdes outfit with detectors for enlisting the fundamental measure and relative moistness. Prior arrangements show that the broadcasting reach diminishes when the potato crop is blossoming. To keep up adequate organization availability, 30 detector TNOdes go about as correspondence transfers. It improves correspondence. The hubs preface at a tallness of 75cm. The detectors introduce at a stature of 20, 40, or 60cm. The gathered information and insights permit us to modify the traversing tree utilized in the remote detector organization and watch its advancement through the analysis. This traversing tree furnishes us with a reasonable contribution for reenacting an isolated detector organization. Insights likewise permit us to find the inactive connections and hubs, check for disappearing hubs because of the broken radio connection.

The low force WSN (Srbinovska, et al. 2015) works from remote hubs kind eZ43-RF2500, from Texas Tool. These hubs incorporate the MSP430 group of ultra-low-power microcontrollers and CC2500 devalued-force broadcasting recurrence handsets. They are appropriate for low force, ease remote practices. The eZ430 RF2500 comprises of MSP430F2274 microcontroller and CC2500 2.4 GHz remote handset. They are the deuce center segments and all the equipment and programming needed for them. The MSP430F2274 microcontroller consolidates 16-MIPS execution with a 200-kbps, 10-digit ADC, and two operation amps, while the CC2500 multiple channel RF handsets intend for low-power remote applications. The ez430-RF2500 target board is an out-of-the-case framework is with the USB troubleshooting interface, as an independent framework with or without outside detectors, or fused into a current plan. The new USB troubleshooting interface empowers eZ430-RF2500 to distantly send and get information from a PC utilizing the MSP430 application UART, alluded to as the application backchannel. EZ430-RF2500 highlights profoundly coordinated, super low force MSP430 MCU with 16 MHz execution, two broadly advanced info/yield pins associated with green and red LEDs for optical input, 21 accessible improvement pins, and an interruptible press button for client criticism.

The commitments of different creators sum up in this segment. Estimation (Goap, et al. 2018) relies upon a blend of coordinated and independent Artificial Intelligence techniques. It uses Support Vector Regression and k-suggests batching to assess the qualification/change in soil (Bogena, et al. 2007) (Cardell-Oliver, et al. 2005) (Hymer, Moran and Keefer 2000) moistness due to environmental conditions. It gives precision and less Mean Squared Error. The Backing Vector Regression model uses data assembled from field devices. The Soil Dampness differences of impending days expectation ready the Support Vector Regression model. The assessment of SMD adds to the k-suggests gathering for improving the exactness of soil soddenness differentiation. It is progressively careful with less Mean Squared Error. The last expected soil sogginess improves quick water framework booking estimation. It adequately utilizes the regular storm information for the water framework. A responsive online interface pictures the expected soil moistness of best-in-class days close by precipitation information and controls the water framework.

The system (Thakur, Kumar, &Vijendra, 2020) finishes by organizing soil suddenness sensor, uninvolved infrared sensor, and Water guide alongside the Arduino board. The work of the soil clamminess sensor is to distinguish the suddenness of the earth and give its respect to the customer. The water siphon will flood the domain exactly whenever the suddenness of soil goes underneath the ideal edge worth. The revelation of interference assessment with the help of the latent infrared sensor completes the task. There is recognizable proof of break in the field of the customers. It will get familiar with it as distributed regards. The game plan is for one month, and data on interference acknowledgment conveniently assembles through the detached infrared sensor. The working of the water siphon oversees without underground bug issues. It helps in immersing the nursery zone. The working of this water siphon is relying upon the sogginess of the soil. The earth sogginess goes underneath to the permits regarding the water siphon starts pursuing the apex assessment of soil clamminess work refine.

The contribution (Keswani, et al. 2019) summarizes the ideal utilization of the water framework by the specific organization of the water valve using a neural construction-based estimate of soil water need in 1 h ahead. It is a water framework control plot. It utilizes an assistant closeness-based water valve.The board segment discovers farm areas having water deficiency. It is a close-by to the examination of smoothing out methods, like variable learning rate incline plunge. It is the best practice to check soil MC on an hourly reason alongside a presentation strategy. It makes the content scattering map. Finally, SSIM list-based soil MC deficiency resolves to control the predefined valves for keeping up uniform water needs through the entire estate locale. The valve control requests to use soft reasoning based on environment conditions showing a system to control the course of action by pondering different environmental conditions. The test site is at Bhubaneswar. It is with a Latitude of 20.351323 and a Longitude of 85.806547 in the eastern space of India. The created farm has a domain of pretty much 5000 m2. The profile involves a layer of wet soil, exceptionally 2 m significant with a sandy dirt surface. Here the dirt quality was found by research focus examination of a faultless illustration of 3.5 kg. The dry mass thickness and consistency of the soil test are about 1.43 g-cm-3 and 0.46 g-cm-3.

The proposed system (Saraf and Gawali 2017) makes the customer improve the quality and measure of their property yield by recognizing encompassing temperature and moisture regards, soil clamminess worth, and water level of the tank from the field with no human mediation.The casing contains sensor units used to secure the continuous characteristics. A pro-center gets and sends acquired information to the control region. A control portion controls the spills for the watering subsystem. Each gadget fuses temperature, clamminess, soil sogginess, and water level sensors similar to a microcontroller and moves trading unit. The recognized data from each center ships off the pro center point by utilizing Zigbee. The data from the expert center point is taken care of at the cloud laborer. The cloud laborer performs dynamic by differentiating between recognized characteristics and predefined limits.After the data planning, the decisive goal at the control region with the help of water framework estimation, the controlling movement transmission to sensor center point follows. The microcontroller controls the exchange trading unit and watering subsystem as requirements are. A revealing structure that is an android application creation passes on late field information to the customer. Furthermore, it demands that customers respond to the primer event, for instance, a rise in temperature and water requirements for plants.

It is a nursery/garden/ranch observing and programmed water system framework (Nawandar and Satpute 2019) equipped for finding the harvest water needs, cautioning the water system unit and client concerning it, giving real-time and history of homestead information. It accomplishes by using water using the assistance of a programmed water system framework for plants by mulling over the plant and soil needs. Bound together Sensor Pole is the mind of the proposed framework uniquely intended for dynamics. The yield subtleties got from the client are taken as the contribution to appraise the water prerequisite. The planting region separates into zones depending on the kind of plants and the region. The territory that gets normal water embeds the sensor, as it can detect prerequisites of close-by zones. Choosing an area that gets less water could prompt overlogging, while a zone that gets more water may make water worry about the harvest. Aside from this calculation, the water system plan assesses when the water system needs to happen for the planted growth. These water system date notes are in a document on USP. This record with the assessed plan is then sent once to the worker utilizing FTP employing the web.

The framework (Rawal 2017) is a mix of equipment and programming segments. The equipment part comprises structure and programming planned to utilize PHP. The website page is on the web. It contains a database where readings from sensors are embedded using the equipment. The dual YL-69 soil dampness sensors alongside LM393 comparator modules are set in various soil conditions for examination. The sensor YL-69 comprises two cathodes. It peruses the dampness content around it. A current passes over the terminals through the dirt. The protection from the stream in the grime decides the dirt dampness. On the off chance it has more water opposition low and in this way increasingly flow will go through. Data from the sensors send to the Arduino board. The Arduino board comprises microcontroller ATMEGA328P liable for controlling the turning on/off of the engine on which water sprinklers. Sensor esteems from Arduino are sent to the GSM-GPRS SIM900A modem. A sim with a 3G information pack embeds into this modem giving IOT highlights to the framework. Qualities are additionally communicated IOT segment through the modem.

The water system gadget contains two sections (Zhao, et al. 2017) - Irrigation Node and Gateway. The water system Node controls the solenoid valve and associates it with the door. It moves signals among workers and the water system hub. It contains four modules- transmitter module, controller module, water system module, and force module. The water system module is the switch of the solenoid valve. The controller module controls it. The control module can execute switch control guidance, track the solenoid valve's state, and interact with the transmitter module through the LoRaWan stack and SX1276 driver. The transmitter module collaborates with the entryway to employ a radio-front (RF) signal. The force module is liable for an electric supplement. It comprises three modules. It advances RF parcels got by LoRa RF handsets to LoRa workers through the UDP interface and sends a message to LoRa RF. The handset demodulates the RF component. The GPS module gives area data. The worker falls into three sections. System Server (NS) is liable for the door convention interpretation as a part that cooperates legitimately with the gateway. LoRa worker is answerable for information reduplication, MIC check, decoding, encryption, and extraction. The LoRa worker gives a bundle type named MAC order configures hubs and entryways in LoRaWAN. Cloud worker utilizes Redis and MySQL to store information. HTTP and MQTT APIs using for both LoRa workers and applications to send or gets information.

The computerized water system (Vaishali, et al. 2017) is an observing framework. It comprises the raspberry pi, water siphon, and dampness, and temperature sensors. An advanced mobile phone module makes correspondence. The yields or plants consider water prerequisites at various stages. The harvests flood as the water necessities at different phases of their development vary. The sensor innovation computerizes the water system improving water use proficiency. The raspberry pi is a single-board PC used to show software engineering. The raspberry pi uses as a PC uses external memory. It has four ports where info gadgets associates. Sensors are the devices changing over the physical boundary into the electric sign. The framework comprises a soil dampness sensor. The yield of the sensor is a simple sign. The sign changes into a computerized sign and afterward took care of the processor. The dampness sensor gauges the dampness substance of the dirt. Copper anodes detect the dampness substance of soil. The conductivity between the cathodes assists with estimating the dampness content level. Blue term is an android application used to compose projects, codes and send these codes to the primary controller utilizing a neighborhood correspondence medium - BLUETOOTH. It sets up a correspondence. Regular orders like passwords, user-names change the design of the Bluetooth module. The RFCOMM/SPP convention imitates linear communication over Bluetooth.

The model (Pernapati 2018) intends to consistently check the weather conditions, the water level, and soil moisturizer. It provides water prerequisites. The framework goes to the critical framework using the Soil Moisture Sensor and declares to the water siphon. The focal part is the ESP8266 NodeMCU Microcontroller.The sensors associates with the ESP8266 NodeMCU Microcontroller. The sensors send the information from their situations to ESP8266 NodeMCU. The controller sends to end clients like a web worker, versatile employing MQTT worker. The Soil Moisture Sensor, Humidity and Temperature Sensor, and Ultrasonic sensor associates as contributions to Microcontroller. The water siphon is associated with means of Relay. The temperature and moistness esteem send to the end client. The dampness sensor senses the water amount in soil, and the water siphon will point to the amount of water in soil diminished.

On the transmitter side (Zhang 2004), a sensor associates with the radio unit through an SIO link. The simple voltage signals from the sensor are digitized and afterward communicated by the coaxial radio wire. On the beneficiary side, the Bluetooth PC card with an implanted receiving wire gets the radio signs and, the PC then measures the crude data. The objective of the estimations was to discover the most extreme radio inclusion range and the ideal stature of the radio unit in various agrarian conditions. The battery life tries. Both the sensor hub and the beneficiary are on two stages at related tallness. The pair of two radio units emanated force. The radio polarization was the like way to guarantee the most grounded signal strength. The BluetoothTM framework utilized in the analysis works in the 2.4GHz unlicensed ISM band. It is a minimal expense, low-force, and short-range radio connection that conveys openings for fast and programmed impromptu associations. Then again, WLANs that work in a similar recurrence range utilize more force with a more drawn-out radio reach and higher information rate. The reflectance attributes of each horticultural field can influence radio proliferation distance. Some of the radio signs are reflected or consumed by the ground vegetation. It causes radio inclusion distinction and affects the limit of the isolated sensor organization. A few sensors are in the dirt, yet the radio units, at rent the receiving wires should be put away from the beginning stay away from close to ground plants.2.4 GHz is the assimilation recurrence of the water particle. The close-to-ground plants may cause incredible way misfortune while the sign is spreading. In any case, the radio unit can't be excessively far starting from the earliest stage. It might build trouble while executing the sensor organization. The ideal stature would be both monetary and radio engendering.

RFID sensor marks (Wasson, et al. 2017) arrange in the domain. The specific province will depend on the field, yields, and restricted sections the agriculturist needs to screen. Observe that sans battery sensor names are not hard to move to start with one region then onto the following. RFID perusers gather ID and sensor data from the field. Sensor data identifies with the ID of the label. It associates robotizing data assembling. When sensors connect with the tag of RFID, they will trade the information about the field to the RFID to trade it to the gatherer. The system straightforwardly gets data from the sensor. An overwhelming data planning programming will segment water and temperature essentials by field runs and pick the measures of water and enhancements the system needs to pass on in each domain for control is in the hand of rancher and sensor will accomplish everything naturally. When the sensor finds a need for water in the homestead, they will tell the rancher about the need for water supply in the yields and it will switch on the valve of water naturally. When the water need is satisfied, it will close the valve as per the condition recognized by the sensor. For instance, if a farmer is not in town, RFID innovation can screen the harvest. IoT is the innovation that expands the restriction of web availability from computerized devices to actual items. It empowers the correspondence between gadgets. It makes the rancher's task simple and less tedious. It additionally saves a great deal of labor and amounts cash. The rancher keeps up his homestead in a more astute manner and increments the creation of harvest to meet the populace's necessities and forestall the abuse of water. It monitors the asset's progressed improvement. Every record trades to the gatherer, and the beneficiary gets the information. The sensor will be turned on the water framework contraption and will pass on the proportion of arrangements to the plants as shown by the regions portrayed by the planning structure. By introducing sensors in the developing industry, creating yields and plants can be hugely improved. The essential inclinations of using an RFID and sensor system are water usage diminishes, crops benefits, and unapproved water use is recognized. Apart from it, rancher work is additionally limited and labor needed for the water system is likewise decreased as all control is in the hand of rancher and sensor will accomplish everything naturally like when sensor find that there is a need for water in the homestead they will advise the rancher about the need for water supply in the harvests and switch on the valve of water consequently and when the water need is satisfied it will close the valve naturally as indicated by the condition recognized by sensor for instance if Famer is of town and nobody is there to the mind of his field now by utilizing sensors and RFID innovation he can screen the yield, as in his nonappearance there is a need of water so he need not be stress as he installed the sensors in a field which will detect the prerequisite so at whatever point crops required water or need a temperature change he will the notice from RFID that there is a need for a supply of water and now rancher needs to tap on the catch and data is the ship of the sensor employing RFID to turn on the water system framework to water the harvests and sensor will consequently kill the switch when need of the yield is fulfilled. So IoT makes crafted by ranchers simple and basic. IoT is the innovation that broadens the restriction of web availability from computerized devices to actual items. It empowers the correspondence between gadgets. The data trades through sensors. It is accessible to the rancher on his gadget. Consequently, it saves a great deal of labor and cash. It makes the rancher keep up his homestead in a more astute manner. It increments the creation of yield to meet the populace's prerequisites and forestalls the abuse of water.

PROPOSED WORK

The creators (Devi, et al. 2020) utilize two strategies. Picture Processing has four stages. Picture obtaining is the way toward getting pictures from various sources. Representation preprocessing improves quality. The undesirable commotion takes out from the derived. Photo Segmentation partitions it into shares. Highlight Derivation takes out the undesirable portion, and just the needed or the sickness bit will be available. AI develops different calculations, takes the information sources lastly predicts the yield. The detectors take every one of the information boundaries and provide the Arduino UNO board, shipped off ThingSpeak worker. At that point, the choice woody plant assorts calculation is the one that anticipates the yield by contrasting the ideal situation and the information situation. The IoT-supported brilliant liquid framework comprises a few parts. In little cultivating fields, natural conditions utilize detectors. The yield peruses an Arduino UNO associated with a Raspberry Pi. The code uses Python linguistic communication, and the information is put away in the SQLite data set. In huge cultivating zones, a remote detector network in which various detector hubs. The yield of the detectors associated with Zigbee for sending information to the door. A Web administration gathers the climate estimating information, and this data is given in these entries HTML, XML design. The Web administration reads the predefined way information utilizing API. The knowledge is in the MYSQL data set and considers in the forecast calculation. This calculation anticipates the dirt dampness and gives the meteorological forecast with the information. It uses the SVR model and incorporates a k-implies grouping calculation.The framework liquid is up to a level with a limit estimation of the dirt dampness. It halts after accomplishing that esteem.

The suggestion diagnoses disease at an early stage. The infection starts with the discoloration of the crop. The image comparison discoloration detection happens after the images are compared with the sampled ones.

Similar kinds of crops show the same behavior in growth, color, size. Their necessities remain the same. They usually require a minimum amount of need w.r.t liquid, sunlight, dampness, and humidity. The previous aggregated crops images are sampled at different stages of growth. The reading w.r.t the needs of the crop is sampled. A threshold is suggesting the minimum and maximum requirements. Before the indicators are deployed the sampled at initial growth is stored. Later stage images are transmitted to the detectors at various stages. These images are used by the detectors with the camera. It takes pictures of the crops and compares them with the stored images. Any variation observed is notified to the server along with the photographs. The system can use a compression algorithm to transmit the images to the server using the cloud.

- Further segmentation and analysis happen at the server level. The segmentation images are compared with the previously stored images (stored on the server) and communicated to the robots to take appropriate measures (in case of infections/disease).
- Other needs of the crops are measured at regular intervals. In case of shortage/excess of these necessities, the same is posted to the cloud. The liquid sprayer uses these measurements.

ANALYSIS

The previous work (Devi, et al. 2020) comprises detectors that can peruse the fundamental measure, dampness depicted object in the grime, and moistness present in the encompassing air. The subsequent one has a camera for sickness location. It exercises picture preparing procedures. Furthermore, the third one comprises robots and agrarian robots for the splashing of pesticides and composts. This detected data is conferred to the simple to-advanced converter through an Arduino and afterward to a Raspberry Pi. The information trades between the Raspberry Pi and the worker. These detectors consistently modify the data of the yield to the rancher. The user takes an essential activity by sending a reacting message. It conveys to the individual gadgets and the individual who worked gadget. The framework carries the harvest to ideal conditions.

The suggestion improves by sampling method. The infection diagnosis occurs at an early stage. Before the indicators deployment, the sampled at initial growth is stored. The picture transmission to the detectors happens using the cloud as the mediator. These detectors use the images to understand the phase of the crop. It compares them with the stored images. Any variation is notified to the server along with the pictures. The system can use a compression algorithm to transmit the images to the server using the cloud. Segmentation and analysis are done at the server level. The segmentation images are compared with the previously stored images (stored on the server) and communicated to the robots to take appropriate measures (in case of infections/disease). Other needs of the crops are measured at regular intervals. In case of shortage/excess of these necessities, the same is posted to the cloud. The liquid sprayer usage in measurements is part of the contribution. NS2 simulator imitates the work. The following parameters are in table 1. Comparison with the past contribution (Devi, et al. 2020), the suggestion has 10.4% early detection. Figure 1 is the representation of the same.

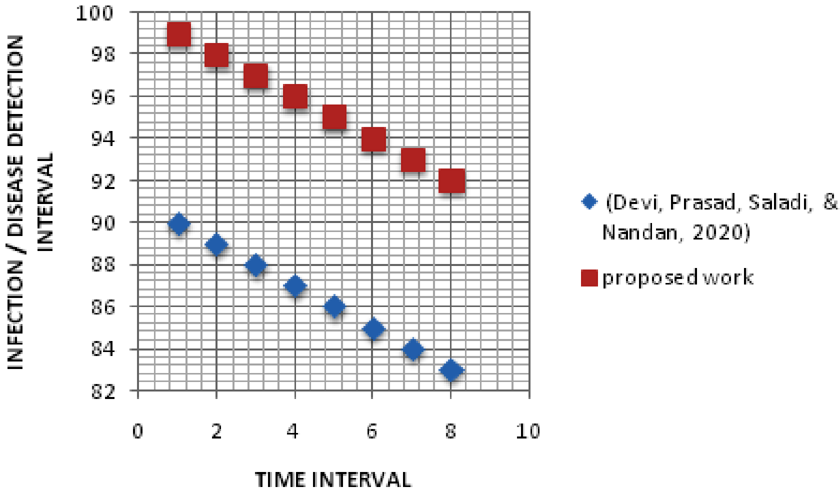

Figure 1. Representation of infection/disease detection w.r.t time.

Table 1. Parametric quantities used in modelling

Parametric quantity	Description
Area of surveillance	200m * 200m
Total amount of detectors positioned	40
Number of clusters	8
Number of nodes having camera	8
Maximum limit of data transmitted per instance	1640 bits (compressed) [1520 bits image + 120 bits information)
Sampled image size stored	13 kb with 120 dpi
Simulation time	60min

CONCLUSION

Detectors are small devices positioned in the surroundings to minimize human efforts. These devices are used in many applications. Agriculture is one such domain that requires its service. The previous work comprises detectors that can peruse the fundamental measure, dampness subject matter in the earth, and moistness present in the encompassing air. The subsequent one has a camera for sickness location.

It uses picture preparation procedures. The third one comprises robots and agrarian robots for the splashing of pesticides and composts. This detected data give to the simple to-advanced converter through an Arduino and afterward to a Raspberry Pi. The information trades between the Raspberry Pi and the worker. These detectors consistently modify the data of the yield to the rancher. The user takes an essential activity by sending a reacting message. It conveys to the individual gadgets and the individual who worked gadget. The framework carries the harvest to ideal conditions. The proposal suggests a sampling methodology to detect the infection at an early stage by 10.4%.

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Chapter 8

APPLICATION OF AGRICULTURE USING IOT: FUTURE PERSPECTIVE FOR SMART CITIES MANAGEMENT 5.0

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ABSTRACT

Agriculture is the most important source of food production. It also plays a crucial role in the gross domestic product of the country. But there are various constraints in traditional methods of agriculture. These

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constraints include excessive use of water during cultivation of crops, time, money, etc.

To overcome the various constraints involved in the agriculture sector, there is a need for an evolved irrigation system. This manuscript aims at developing an automated smart irrigation system with the help of the internet of things. It aims to maintain an adequate amount of water needed by the crop by monitoring the amount of soil moisture, temperature, and humidity in the soil. Data of temperature and humidity is maintained in the database for backup. The data is used for crop rotation and also helps the farmer with the selection of appropriate crops. We can also verify the different types of soil appropriate for different crops using this model. These will also benefit the farmers as they will be able to monitor the irrigation of the crop from a distant location. It would also save the time of the farmer and reduce the labor work.

Keywords: Arduino, soil moisture sensor, humidity and rain sensor, ESP8266 wifi module, DHT-11, smart irrigation, IoT

1. INTRODUCTION

Agriculture can be defined as a technique of cultivating the soil, growing crops, and raising livestock. Agriculture is considered the main source of food and fabrics. Cotton, wool, paper, and leather are all agricultural products. Agriculture also provides wood for construction materials and other household activities. Before agriculture became an important factor people used to spend most of their lives searching for food and hunting wild animals. But around 2000 years ago agriculture became the most important source of food and most of the Earth’s population became dependent on agriculture.

1.1. Water Crisis in the World

Water is the basic need of every living being in this world. It plays a vital role in carrying out day-to-day activities in human life. Agriculture is an area where water is required in a large quantity for better growth of crops. But due to the overuse of water, the groundwater level is depleting very rapidly. The main reason for this problem is the population growth and its increasing demand for water requirements. Overconsumption and wastage of water is another major problem that is leading to the water crisis in this world. Water crisis may lead to economic decline and poor living conditions if we continue the current scenario of water usage (Sahu, T. et al., 2017).

1.2. Global Warming and Its Impact on Agriculture

With the estimated growth of the world's population to 8 billion by the year 2050, the requirement for crops and food will also increase rapidly. On the other hand, the temperature is likely to increase by 4 to 5 degrees in the next few years due to global warming. Some climate models describe that there would be an increase in the concentration of carbon dioxide on the crops. Therefore, climate change has the potential to affect the productivity of agriculture. It is expected that there would be an increase in yearly dry days to about 15 extra dry days in the next few years. The experimental results indicate that the dry areas would likely receive less rainfall throughout the year. This will have a direct impact on the total growth of Agriculture (Barkunan, S. R. et al., 2019).

1.3. Need for Water Conservation

Water is considered the most important substance for running our life properly. Our bodies need water to function properly. According to science, humans can survive for weeks without food but can survive only a few days without water. But we humans are depleting the freshwater sources very rapidly because we are not bothered to use the water efficiently.

The Earth's temperature is rising due to global warming and the hotter the earth will be the more would be the water demand. The shortage of water will lead to less production in the agricultural field and thus the water crisis will become a food crisis. The main source of fresh water is groundwater which is decreasing very rapidly. The groundwater level could be increased by using the Technique of rainfall harvesting (Math, A. et al., 2018).

1.4. Smart Irrigation Devices

Smart irrigation devices are components used in this research work which will first analyze the climatic conditions like rainfall and temperature and then they will automatically operate the process of irrigation.

Devices like rainfall, temperature, and humidity, and moisture sensors can give precise values which are used by Arduino to carry out the automated irrigation process. These values are used to match the threshold values and then the water pump is turned ON and OFF accordingly. Thus using these smart irrigation devices we can reduce water wastage as well as increase productivity (Yamini, R. et al., 2018).

1.5. IoT and Smart Irrigation

IoT abbreviates to the Internet of Things. IoT is considered a milestone when we talk about the evolution of superior technology. IoT comes into mind when we try to automate things. IoT can be applied in various sectors such as home automation, surveillance systems, and in the agriculture sector, there is a wide range of applications of IoT. As we already know that the crops require proper care for better yielding and irrigation is the most dominating factor that affects it most. Due to irregular monsoon, cultivated plants do not grow properly and result in low production. Using advanced technology like IoT we can overcome this problem. By planting different sensors in the field we can record important factors like temperature, the humidity of the air, and soil moisture content and make decisions accordingly using microcontrollers. Irrigation will be done automatically when the moisture of the soil falls. It will be more helpful in the areas where there is a lack of water supply and fewer rainfall readings. The use of IoT in an irrigation system can bring a new revolution in the agriculture sector (Amalraj, J., Jegathesh, et al., 2019).

1.6. Use of AI and ML in Agriculture

In this fast-growing digital world, we have thrust our thinking limit and are trying to replace normal brains with artificially created one. Using AI we can make an intelligent machine. Machine Learning with deep learning, ANN, CNN can intensify the machine work which results in the development of more superior technology. The use of AI and ML in the agriculture sector can bring revolution and give birth to a happy and prosperous era. Using AI and ML we can make a system smart enough that can act on its own and water the field when needed. We can also develop a system smart enough that can monitor the condition of crops and inform the former who can act accordingly, which finally results in good production (Dharmaraj, V., et al., 2019).

1.7. Sensor-Based Irrigation and its Significance

The soil moisture of the field can be figured out by various techniques such as by using the thermo-gravimetric method or by using a gypsum block and tensiometer methods. These methods are old and are put back by Time Domain Reflectometry, Frequency Domain Reflectometry, and optical sensor technology. Soil moisture estimation based on sensors provides real-time data, at an affordable cost. Sensor-based irrigation has a lot of positive points over the traditional method. It collects data that is real-time and can be interpreted accordingly by different smart modules. It is cost-efficient and time-saving. (Gupta, Lav, et al., 2019).

- Productivity increase
- Less water consumption
- Almost zero manpower consumption
- Cost-efficient
- The system has weather resistance
- Most efficient use of water

1.8. Existing Smart Irrigation Systems in the Market

- Drip-irrigation System (Traditional): The most efficient way of irrigation is the traditional drip irrigation system. It allows water to ooze at the plant roots, resulting in less water wastage. It also helps in the efficient utilization of fertilizer which is absorbed by soil uniformly with steady irrigation (Amalraj, J., Jegathesh, et al., 2019).
- Irrigation with Timer System: The best way to reduce water wastage in irrigation is by making a schedule. An irrigation system with an automatic timer can prevent over-watering in the field and can prevent damaging the crop due to excessive irrigation. It helps to manage the water requirement for each season. It is cost-efficient and reduces wastage of water while irrigation (Amalraj, J., Jegathesh, et al., 2019).
- Smart Irrigation System: It uses MATLAB along with wireless sensors and IoT. Very good for water usage optimization and can be operated remotely. It has auto and manual modes which are very helpful and cloud implementation makes it highly applicable (Amalraj, J., Jegathesh, et al., 2019).

2. LITERATURE REVIEW

The paper by Bobby Singla and others tells about how we can effectively control the water supply in our agricultural field. Sensors that are used for this application are the DTH-11 sensor and soil moisture sensor. The information is provided on farmer mobile phones using Wi-fi and Arduino. In this research paper, the DTH-11 temperature sensor and soil moisture sensor are connected to the input pins of Arduino Uno. The analog values produced by Arduino Uno are converted to digital output by the microcontroller. The obtained values are displayed by the mobile application. The motor is switched on/off based on the value obtained from the microcontroller with the already defined threshold value. The above system is found to be efficient in reducing the cost of the farmers and optimizing their agricultural production. The maintenance required by the system is also less (Singla Bobby et al., 2019).

Rawal, Shrishti, and other teams have found in their paper propose an irrigation system that maintains and decides the required soil moisture content through automatic watering. The value obtained from soil moisture sensors helps to determine the exact quantity of water needed for irrigation. The system is divided into hardware and software components. Hardware comprises systems such as sensors, Arduino-UNO whereas the software consists of a webpage displaying the data from the microcontroller. The sprinkler control is achieved using a threshold value. The value obtained from the system decides whether to turn on/off the sprinkler. The reading obtained is then put forward on the farmer’s website. The system uses values obtained from the microcontroller to on/off the sprinkler. This prevents the loss of the farmer and thereby avoiding crop damage (Rawal, Shrishti, et al., 2017).

Nandhini, R, and their team of researchers revealed that the proposed irrigation system helps to regulate the flow of water in the system. By using these systems we can make effective use of water. The system uses soil and humidity sensors to find the level of moisture and humidity in the soil. The sensed values are then displayed on the screen. This system also uses various sensors such as pH sensor, pressure sensor, DTH-11 sensor to find the sensed values from the Arduino UNO. The sensed values are then sent to be displayed on the screen of the web page application. If the value on the sensor crosses the threshold value then the pump is turned on/off automatically. The main objective is to find an effective, user-friendly solution to the given problem. Due to readily available updates from the server, users can know about crop fields anytime (Nandhini, R. et al., 2017).

In their experiments of agriculture, Aman Kumar and the team proposed that their system is an automated irrigation system designed to save the time, power, and money of the farmer. By using these systems we can make effective use of water. The system uses soil and humidity sensors to find the level of moisture and humidity in the soil. The sensed values are then displayed on the screen. The sensed values are then sent to be displayed on the screen of the web page application. If the value on the sensor crosses the threshold value then the pump is turned on/off automatically. The main objective is to find an effective, user-friendly solution to the given problem. Due to readily available updates from the server, users can know about crop fields anytime (Kumar, Aman, et al., 2017).

3. Components Used

3.1. Arduino System

Arduino UNO is a microcontroller that has both hardware as well as software components. Multiple sensors could be connected at a time to the Arduino board and these sensors gave values to Arduino with the help of program codes. The Board also consists of LED which glows when our values are matched. We can run Arduino either by connecting to our computer or by using a DC power supply. The main concept is to run a physical device by using the software. With the help of programming, we can easily automate various devices using Arduino. An Arduino board generally consists of Analog and digital pins, a USB port, a power jack as well as a reset button. (As per Figure 1) (Yamini, R. et al., 2018).

Figure 1. Basic Arduino Uno, microcontroller (Yamini, R. et al., 2018). https://store.arduino.cc/usa/arduino-uno-rev3.

3.2. Sensors Used in Our Research Work

In this project, we are using 3 types of sensors to calculate the soil as well as atmospheric conditions. Sensors used are soil moisture sensor, humidity, and temperature sensor as well as rainfall sensor.

3.2.1. Soil Moisture Sensor

The moisture of the soil plays an important role in the irrigation of a field. The soil moisture sensor is a kind of sensor that is used to measure the content of water within the soil. The moisture of the soil is dependent on the amount of water within the soil. If the soil is dry it will have less moisture as compared to the wet soil. The moisture sensor works by inserting it into the field and the water content in the soil is reported in the form of a percentage. There are multiple uses of soil moisture sensors:

- Agriculture
- Landscape Irrigation
- Research (As per Figure 2) (Yamini, R. et al., 2018).

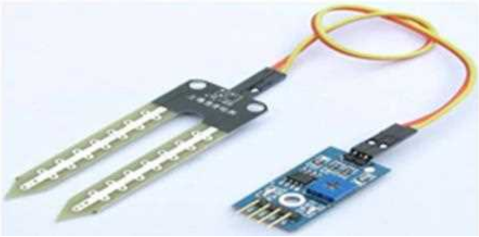

Figure 2. Soil moisture sensor (Yamini, R. et al., 2018) https://images-na.ssl-images-amazon.com/images/I/51CEr20GRdL._SX342_.jpg.

3.2.2. Temperature and Humidity Sensor

Temperature and humidity sensor (DHT11) is a combined low-cost sensor that gives values for both temperatures as well as humidity in the environment. It works by inserting the sensor into the Arduino board and it gives climatic conditions of the surroundings. Humidity measurements do not mean to measure humidity directly; rather they depend on the measurement of quantities such as temperature, pressure, mass, resistivity to calculate humidity. These sensors give the output as digital values which make them easy to interface and use with microcontrollers such as Arduino, Raspberry Pi boards. (As per Figure 3) (Yamini, R. et al., 2018).

Figure 3. Temperature and humidity sensor (Yamini, R. et al., 2018) https://www.electronicscomp.com/dht11-temprature-humidity-sensor-module-india.

3.2.3. Rainfall Sensor

The rainfall sensor is a device that is used to calculate the amount of rainfall in a particular area. This sensor is used as a water preservation device and this is connected to the irrigation system to check if there is rainfall going on and if the condition is true, it shuts down the system at the time of rainfall. This sensor includes a board with nickel-coated lines and it works on the resistance principle. When the rain droplets fall in the nickel-coated board it gives the value of rainfall in the area. The 4 pins of the sensor are inserted in the Arduino while the board is kept in the field to calculate values (As per Figure 4) (Yamini, R. et al., 2018).

Figure 4. Rainfall sensor (Yamini, R. et al., 2018) https://electrosome.com/interfacing-rain-sensor-arduino/.

4. PROPOSED SYSTEM

Various sensors, microcontrollers, the android application can be used for making an automatic irrigation system. We generally go for low-cost humidity, temperature, and soil-moisture sensors. These sensors are connected to Arduino and continuously monitor the field.

The collected data by the Arduino through sensors are transmitted to the user wirelessly so that they can control the system remotely. The smart android application compares the value received from the sensors from its database and takes the appropriate decision. The proposed system has two modes auto and manual.

When the auto mode is on the system acts automatically without any human interruption while with manual mode ON motor can be operated with just a click of the switch. The motor toggles accordingly with soil moisture value, if the value is below the threshold motor turns ON else remains in an OFF state.

The sensors are joined to the Arduino Uno and the hardware communicates through a microcontroller (ESP8266) which is a wi-fi module. All sensor values are displayed on the mobile interface so that the user has a continuous reach of the condition of the field. Programming of Arduino Uno is done in Embedded C.

We program the board that transmits the sensor value and motor condition to the user and can also control the motor when the Auto mode is engaged. The coordination of four sensors and the motor is controlled by the program fed on the board. The system continuously monitors the soil moisture content and keeps sending it to the user, if the sensor gets low reading it turns the motor on, and on reaching the requisite state it turns it off. All these functionalities are governed by a set of code fed on the board.

The user and board communicate via the wi-fi module (ESP8266). It has a quite considerable range. The threshold value will be set in the board and android application.

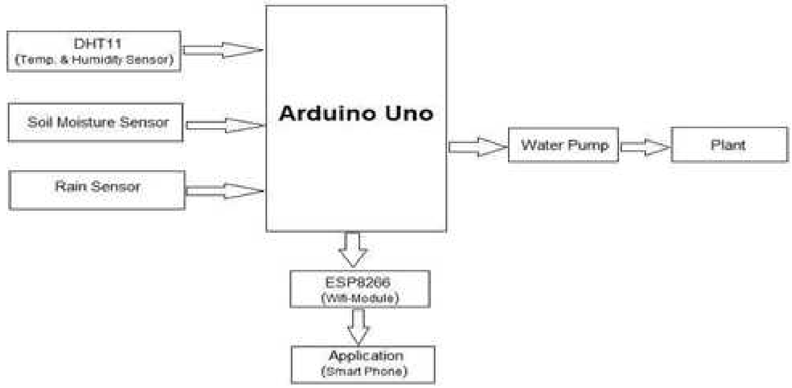

Figure 5. Block Diagram of Smart Irrigation System Using IoT: Future Prospective for Agriculture.

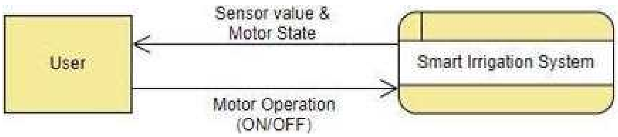

Figure 6. Data Flow Diagram of Smart Irrigation System Using IoT: Future Prospective for Agriculture (Level-0).

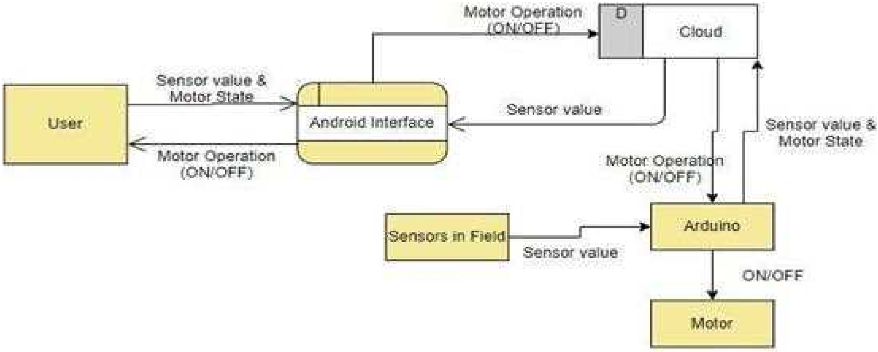

Figure 7. Data Flow Diagram of Smart Irrigation System Using IoT: Future Prospective for Agriculture (Level-1).

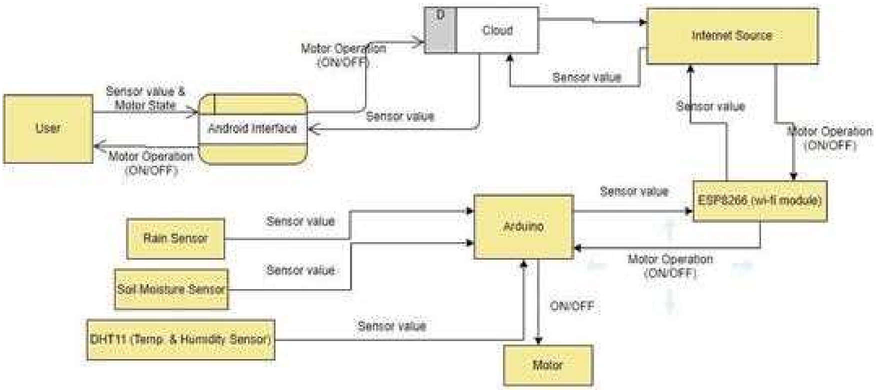

Figure 8. Data Flow Diagram of Smart Irrigation System Using IoT: Future Prospective for Agriculture (Level-2).

The moisture of the soil will be different in the winter and summer seasons and also the humidity and temperature. The threshold value is formulated after the consideration of different environmental and climatic conditions. The system turns the motor on automatically if the reading goes below the threshold and vice versa. Former can also operate the motor manually using the android application. Below are the block diagram and data flow diagram of the proposed model (Pl. refer the Figure 5 to Figure 9 for the different diagrams of our proposed model).

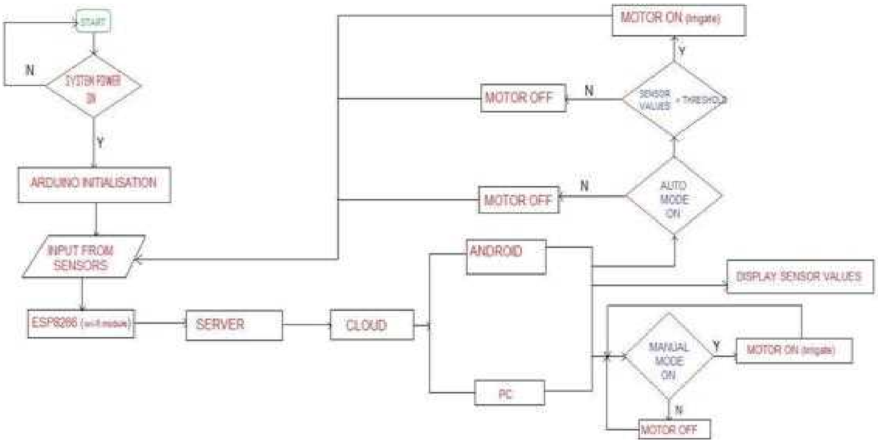

Figure 9. Activity Diagram/ Flow Chart of Smart Irrigation System Using IoT: Future Prospective for Agriculture.

5. ANDROID MOBILE APPLICATIONS FOR SMART IRRIGATION

The Android Mobile application is used to automate the activity of irrigation. The application's user interface consists of a Login page where the farmer has to enter the login credentials to enter the main functioning page. The farmer first has to create his/her account to use the application. This is an extra security feature added so that nobody can misuse the system. There are two options on the login page, one to sign up and the other to log in. If the user is new he/she first has to make his account and then he will be able to log in successfully. (As per Figure 10).

Figure 10. Login Page of the app of Smart Irrigation System.

5.1. Main Page

Figure 11. Home Page of our working App after successfully logging in from the Login page the farmer will be able to access the main page of the application. Here on this page, all the values from the sensors would be displayed. If the farmer wants to manually operate according to the current values then he can manually turn the ON/OFF button or he can use the Automation button which will automatically turn the motor ON/OFF when the Threshold values are matched. (As per Figure 11).

5.2. Snapshot of Working Model (ICs and Working model)

In this project, multiple sensors are connected to the Arduino board which will give their respected values when inserted in the field. We will program the Arduino in such a way that it will automate the process of irrigation.

The user's job is to only start the motor pump or if he desires he can switch off the motor with just one click.

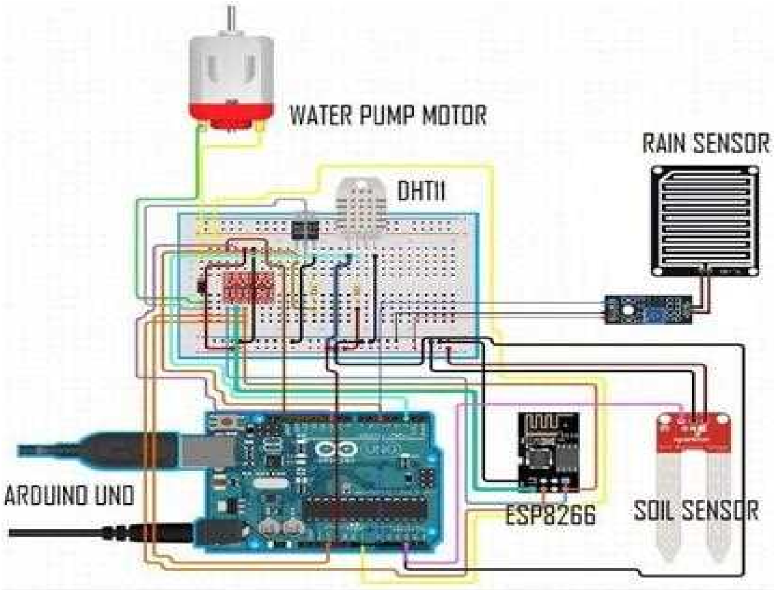

Figure 1.12. Proposed system of Smart Irrigation System Using IoT: Future Prospective for Agriculture.

On starting the Motor pump the following conditions will work:

1. The user can switch OFF the motor manually with the help of an android application.
2. The motor pump will automatically get switched OFF on reaching the threshold value of soil moisture.

3. If it is already raining in the field then the motor pump will automatically turn OFF because watering the field is not required if it is raining outside. Once the rain stops and the conditions go under the required threshold value then the motor will again turn ON. This helps in saving water resources and electricity (As per Figure 12).

6. Novelty

There are many smart irrigation projects available in the market but they are generally very expensive and they work only for a bigger region whereas this project can also work for a small land and it is also inexpensive and efficient as compared to other projects. With the factor of low cost, any farmer could easily buy and use it. It is also very simple in design and working is also very easy as compared to other projects so it can be used by anybody. The maintenance cost is also very low. The project aims in reducing water wastage while working efficiently.

7. Future Research Work

The proposed model is highly effective and is cost-efficient. It will be more effective when used along with the drip-irrigation system. There are a lot of possibilities in this model. Research can be done to make it more cost-efficient using alternate semiconductors, the interface can also be enhanced and more functionality can be added. There is a possibility of improving the server connectivity which will be very beneficial. By applying different AI and ML algorithms it can be made more advanced. Overall the model is more than enough and can be advanced with future work and research as there are always possibilities for improvement.

8. Limitations

Apart from the advantages, it has its limitations. The ICs are not much compatible with the weather and require waterproof protection which increases the cost. We have to use multiple sensors to record value as it has a small range so there are possibilities of human error while implanting the sensors. Sometimes sensors do not work as expected which requires proper attention to good, and precise results. With proper knowledge and skill, this mode can be beneficial to the agriculture sector. The limitations of the model can be reduced with good research work.

Conclusion

The above-proposed model Smart Irrigation System Using IoT: Future Prospective for Agriculture is much realizable and cost-efficient for less consumption of water while irrigating the field. This system is very beneficial in the region with less rainfall hence helps in sustainable development. Irrigation of the field can be done in a much smarter way using this model. This model will be very useful in minimizing the consumption of water while irrigation and the saved water can be used for other purposes which results in the conservation of water. This model is eco-friendly and does not harm the field in any way. With multiple sensors, we can locate the area which requires water and irrigate that area only. It requires less maintenance and is highly effective in the reduction of water consumption. With proper irrigation the productivity increases and results in greater profit. The future work is to make the interface much more detailed and add more functionality to the system.

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Chapter 9

THE INTERNET OF THINGS (IOT) FOR SUSTAINABLE AGRICULTURE

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ABSTRACT

Increasingly, agriculture is becoming more knowledge-intensive. The challenge of feeding the ever rising population will not be an easy task. Most of the food consumed in developed nations is from half a billion small family farmers. For future food and nutritional development, their role is very important. Yet, the information on

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various inputs and other opportunities are often limited. For sustainable agricultural growth, improved access and availability to information and communication technologies (ICTs), especially cell phones, computers, radio, internet and social media, has created many more opportunities for multi-format information gathering, processing, storage, retrieval, management and sharing.

Keywords: IoT, weather, sustainability, agriculture

INTRODUCTION

Agricultural production depends on many variables, the main factor being weather. Weather varies with space and time; its forecast can also help to reduce farm losses by proper agricultural operations management. It is not possible to fully prevent all farm losses due to weather conditions, but it can be reduced to some degree by making changes through timely and reliable weather forecast details. Agromet's weather forecast and weather-based advisories help to increase the economic gain of farmers by recommending effective management practices in compliance with weather conditions.

The success or failure of the production of agricultural crops is determined primarily by weather parameters. Via its impact on soil and plant growth, weather manifests its influence on agricultural operations and farm development. A large portion of the overall annual crop losses are due to aberrant conditions. The loss could be reduced by timely and reliable weather forecasting by making changes to the coming weather. With the aid of advanced weather forecasts, agricultural operations may be advanced or postponed for three to ten days [1]. Not only is an agricultural forecast useful for the efficient management of farm inputs, but it also contributes to reliable impact assessments.

Weather is one of the most significant factors deciding agricultural production's success or failure. It has an impact on any stage of plant growth and development. Any weather variability during the crop season, such as monsoon delay, excessive rains, floods, droughts, too-high or too-low temperature spells, will affect crop growth, and ultimately the yield quality and quantity. With timely and reliable weather forecasts, crop losses can be minimized by doing proper crop management in time [2]. The weather forecast also offers guidance on the selection of crops best suited to the climatic conditions predicted.

The aim of the weather forecast is to inform farmers on the real and expected weather and its effect on the different daily farming operations, i.e., sowing, weeding, pesticide spray time, irrigation scheduling, application of fertilizer, etc., and overall crop management. The meteorological forecast contributes to increasing agricultural production, reducing losses, risks, and input costs, improving yield, labor and judicious use of chemicals [3]. Efficient information on climate and weather enhance the production of crops, livestock and fisheries. Advisory services on weather and environment will enhance farmers' management which reduces risks and costs, improves productivity and quality; conserve natural resources and reduce pollution. ICTs are seen as an essential way for such a transition to be accomplished. The agricultural extension oriented ICT leads exciting opportunities to allow farming communities to be empowered.

ICT IN AGRICULTURE

ICT is a concept that focuses on utilizing and incorporating information technology (IT) communication systems. It applies to any system or product allows 'electronically recording, storing, transmitting and displaying data and information.' This includes internet and all hardware and software for computers, radio, digital television, cellular networks, mobilephones, and satellite systems. The power house of global economy recognized it the main stream development instrument for raising citizens' economic and social status [4]. With out its integration, countries or regions have no chance of solving the problems and challenges.

In agricultural, industrial and social sectors, it can form and enhance wide range of developmental applications and affect all sections of society. For human development, ICT offers unique opportunities. It refers to any electronic means of information collection, retrieval, storage and dissemination. For all attempts to bring about a social shift, communication is important. The advent of ICT has allowed a rapid pace of collaboration, interaction and data that has had a greater effect on society [5].

ICT is a diverse collection of technical tools and resources for knowledge creation, distribution, storage, added value, and management. In particular, advances in Information and Communication Technology (ICTs) and the Internet have revolutionized the entire field of agriculture, creating new markets, altering the structure of the distribution systems for agriculture and re-engineering all processes [6].

During the last two decades, there has been a great deal of interest in understanding the capacity of information and communication technologies (ICTs) to achieve socio-economic growth. This resulted in studies on agriculture, health, government financial services, education and jobs with different ICTs and their implementations. Many of these programs clearly show the tremendous potential of ICTs to enhance the quality and effectiveness of delivering accurate information to communities.

ICTs in recent past encouraged management expertise and fostering creativity in agriculture sector. ICT-based extension advisory methods include providing localized and tailored advisory services; assisting management; extension actors to collaborate on innovation; and social media promoting growth [7].

ICTs not only encourage scientists and extension practitioners to exchange knowledge, but also enable farmers to connect better returns to the market and consumers. It also provides farmers with the ability to share their farming practices and challenges. ICT needs to be harnessed by all the players for agricultural production. Technological applications can hit millions of farmers, stakeholders and rural areas and serve as a catalyst for social change and for food security.

INTERNET OF A THING (IOT) IN AGRICULTURE AND ALLIED SECTOR

The global recession's revival has created ripples across both developed and emerging economies. To ensure global food security, the agricultural sector would have to be even more productive and resilient. Together, modern-day agriculture and society demand increased food production to feed the global population. Some farmers' problems can be mitigated to accomplish this goal; automation and smart decision making are also becoming more important. The Internet of Things (IoT), pervasive networking, ad-hoc wireless and sensor networks, radio frequency identifiers, cloud computing, remote sensing, etc., are becoming increasingly common in this regard [8].

In the field of agriculture and improve productivity, convergence in agriculture pushes smart-agriculture. Agricultural applications include greenhouse climate, animal monitoring, and so on. For the items potential benefits of IoT have been identified by the Global ICT Standardization Forum for developing and under-developed economies as operation, clarity details, improved quality, and precision are important.

Global-intercommunication in corporate pervasive connectivity, computation and environmental intelligence, IoT is a vision in which 'things' can be recognized, addressed and/or regulated through the internet particularly, automobiles, etc. This will form the basis for a wide variety of new technologies, control, or protection [9]. By integrating technological advances in item recognition ('tagging items'), stuff items can link the world's artifacts way advantages:

1. Improved efficiency of inputs for use (soil, water, fertilizers, pesticides, etc.).
2. Reduced production costs.
3. Augmented profitability.
4. Sustainability.

5. Safety in food.
6. Environmental security.

IoT has the power to change the world ways of living; with more productive factories, more connected vehicles, and smarter communities. So the agricultural industry needs to accept the food resolve issues and rising severe effects of agricultural practices that can be resolved. Smart farming can reduce the waste produced, boost may used for the amount of trips take by farm vehicles [10]. Smart farming, then, is simply a high-tech food growing method safe both and into agriculture ICTs.

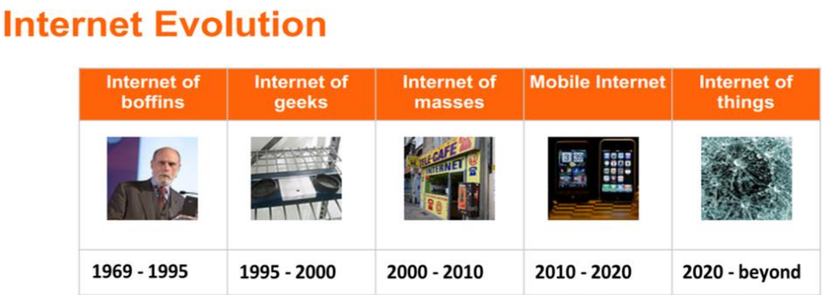

Figure 1. Internet Evolution.

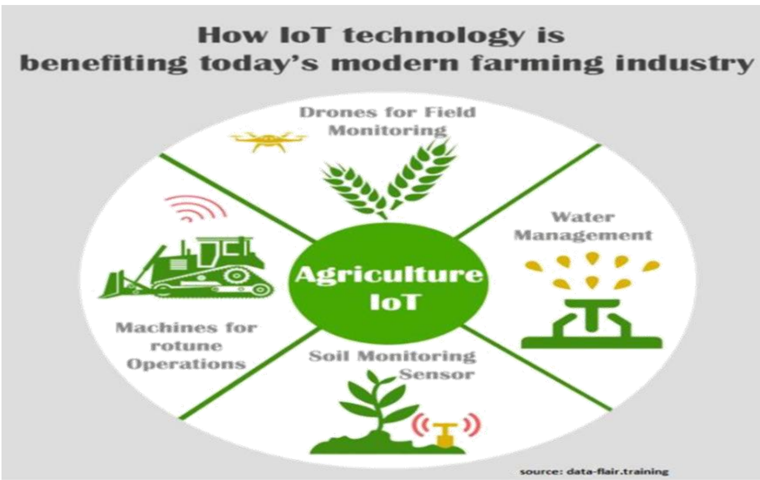

Figure 2. IoTs and Today's innovative farming industry.

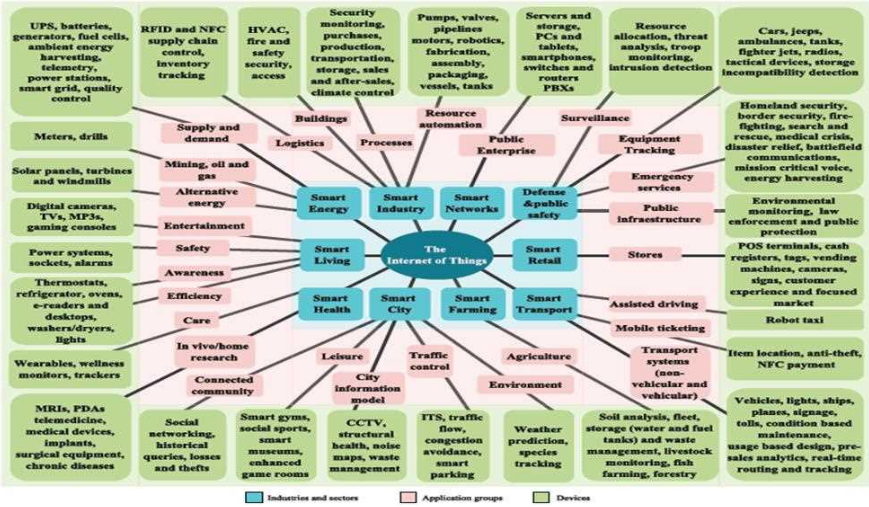

Figure 3. IoT proliferation.

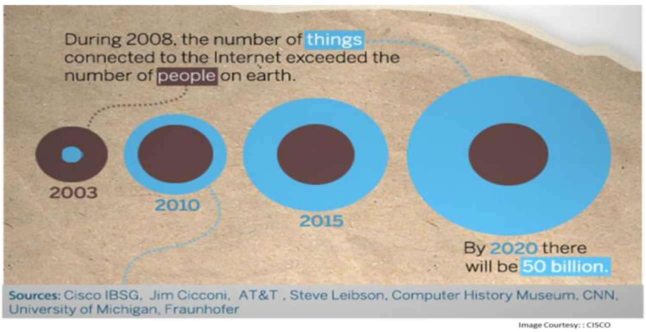

Figure 4. People to IoTs ratio.

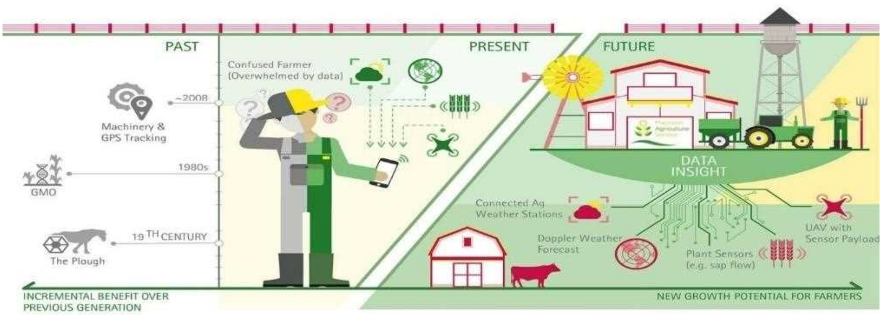

Figure 5. (Continued)

Figure 5. The future of Agriculture with IoT.

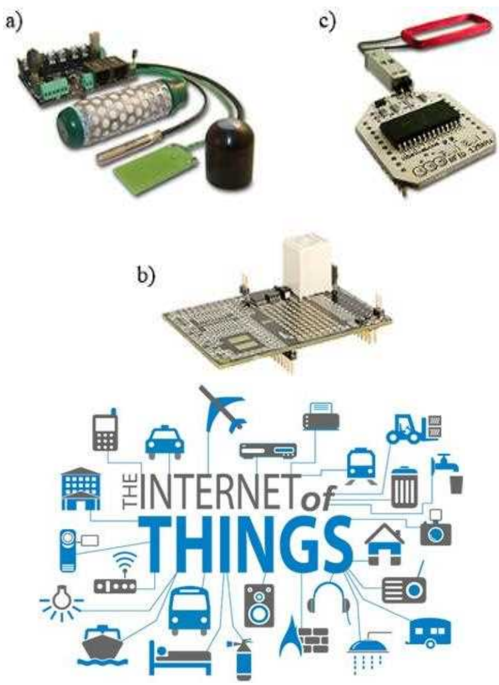

Figure 6. (Continued).

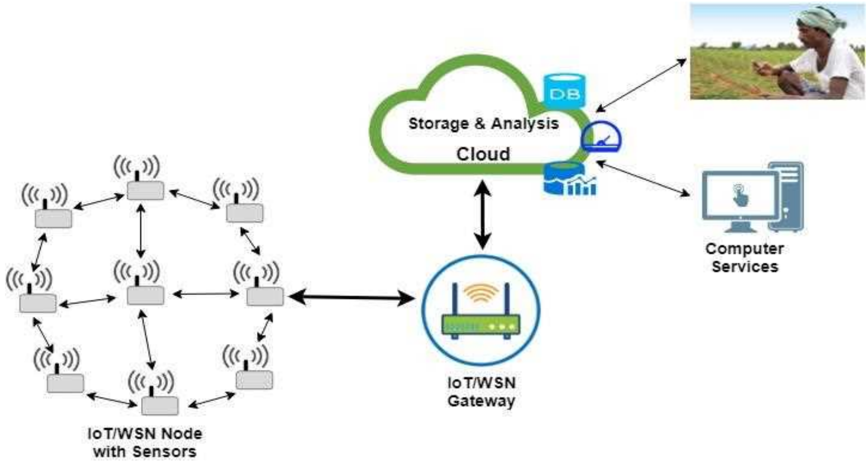

Figure 6. The general system architecture.

IoT agriculture applications include:

1. Precision Farming: It is a system or practice that makes the farming process more precise and regulated. Main components of this approach are cameras, autonomous vehicles, hardware, systems, precision agriculture and common IoT.
2. Agriculture Drones: This is a good example of today's agriculture incorporated in ways of evaluation introduced, the advantages brought by the use of interactive/improved use of focused farming, and choose the extracted observations on various calculation. During the flight, the drone captures photographs and position initially took.
3. Livestock Monitoring: This allows the state of livestock, such as identifying infected and isolated livestock. This helps to minimize costs. Among the many alternatives offered, their water splits input submitted helps to concentrate more.

4. Smart Green houses: This process increases grain, fruits, vegetables, etc by ways of manual intervention through mechanism approaches. In order to control environment, different sensors are used. Cloud server assists and control action. IoT sensors are solar powered, monitored on line and provide information on temperature, strain, humidity and levels of light.

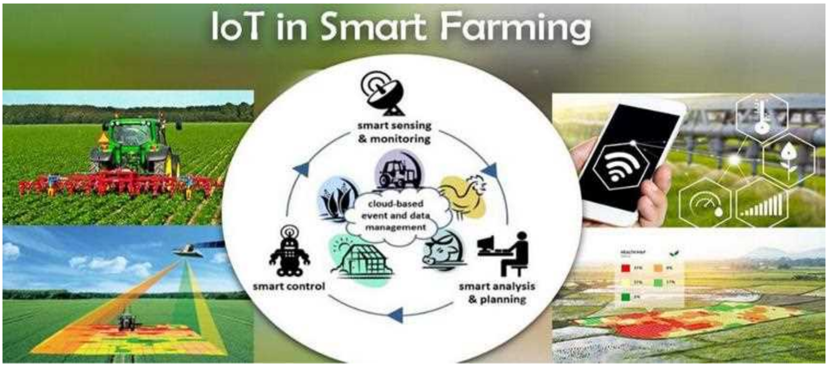

Figure 7. IoT in smart farming.

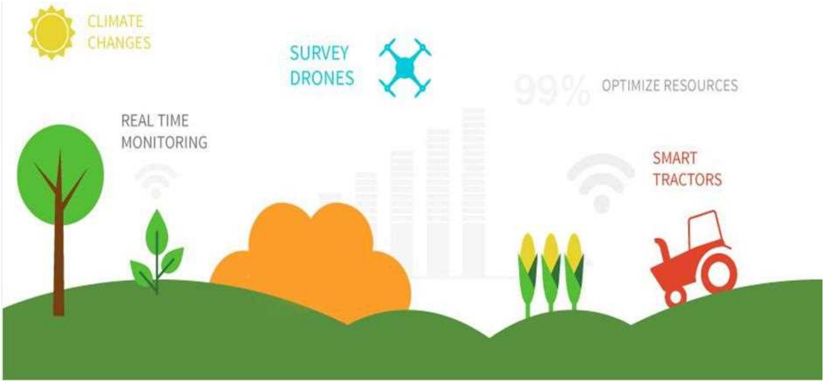

Figure 8. Agricultural drones.

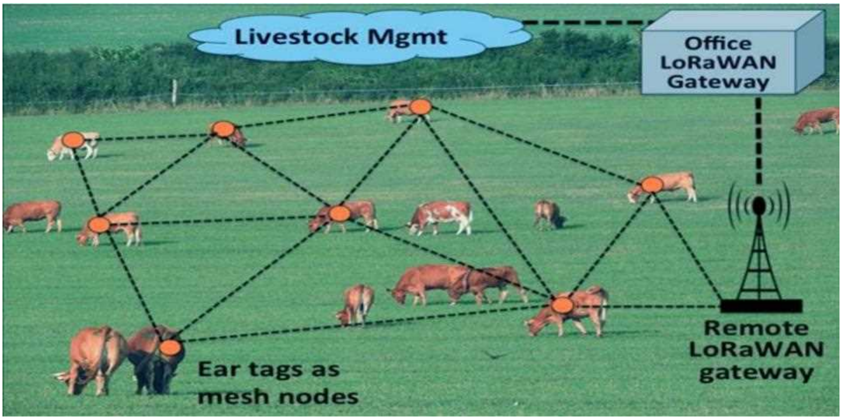

Figure 9. IoT in livestock Management.

Figure 10. Smart green house.

GEO-SPATIAL TECHNOLOGY

Geo-spatial technology refers to the simulation, calculation and study, using specialized equipment, of the characteristics of the earth or other natural phenomenon viewed from space. RS-GIS and GPS are the fundamental components involved in this technology that enable the creation of a Decision Support System (DSS) with regard to the dissemination of data or information produced. For the visual analysis of geo-spatial features using satellite sensors and the interpretation of image data, space-based technology like remote sensing has been adopted.

Geo-spatial characteristics and their suitable locations provide a forum for companies' indifferent fields to develop, and many organizations are interested in using this technology to improve their business or research work.

In any given geographical location, produced and stored data regarding geo-spatial characteristics have a strong visual impact displayed through maps, and maps play a vital role in monitoring and quantifying change over time [11]. The technology of remote sensing and GIS (Geographic Information Systems) is directly and indirectly involved in developing geo-spatial information and geo-data base management. RS-GIS have provided a single window forum for the dissemination of geo-spatial features relevant to farmer advisory services under the Information and Communication Technology (ICT) mode.

1. Remote Sensing (RS): RS has many uses and the art and science of collecting knowledge about surface of earth without making any direct interaction. This is achieved by detecting and recording energy that is reflected and released.

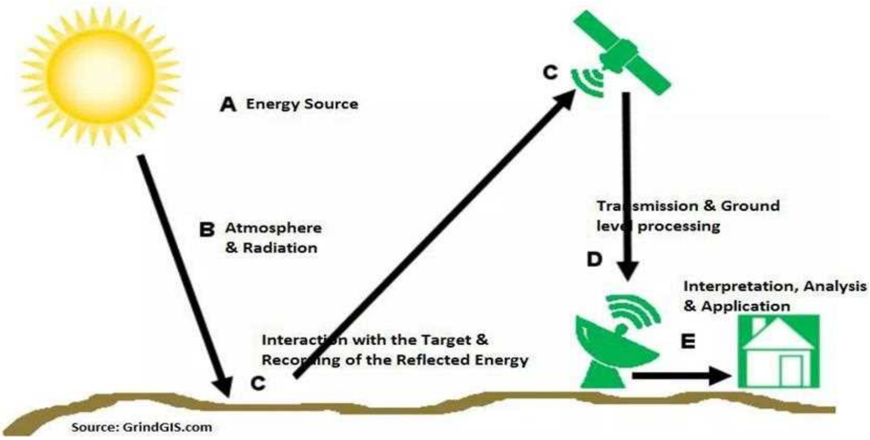

Figure 11. Remote sensing.

The applications are very diverse and referred here as digital satellite image analysis:

a) Identification of crops: The crop observed has features and laboratories analyzed different aspects.
b) Estimation of crop acreage: Estimating agricultural land on which a crop has been planted done due to this is typically a tedious operation.
c) Identification of planting and harvesting dates: With variables identification and forecasting of planting, harvesting seasons of each crop, weather patterns and soil types are done.
d) Assessment of crop condition and stress detection: Each crop's status and the degree to which stress has been withstood by the crop are assessed. To assess quality, this information is used.
e) Drought monitoring: This is to track weather patterns in a given region including drought. The data can be used to forecast patterns, precipitation and precipitation.
f) Modeling estimation of crop yield: This is used to assess estimated average yield.
g) Forecasting: Production and yield required of the crop over a given region and to determine how much of the crop will be harvested under particular condition. The quantity of crop to be produced over a given period of time in given farmland can be predicted.
h) Development: Remote sensing technology can be used to reach the farm land in the event of crop damage or crop growth, and to assess precisely how much of the donated crop was destroyed and the development of the remain crop on the farm.
i) Horticulture, cropping systems research: Different remote sensing technology has been used mostly to forecast.
j) Soil moisture estimation: Soil moisture can be difficult to calculate. Remote sensing provides information about soil moisture and helps to assess the amount of moisture in the soil and type of crop that can be grown in soil.

k) Control of irrigation: RS provides details about the amount of soil moisture. This knowledge is used to assess whether or not a given soil is deficient in moisture and helps to plan the soil's irrigation needs.

l) Mapping: Remote sensing is a most significant application where farmers are able to tell what soils are suitable for crops and what soils need irrigation. In precision agriculture, this knowledge helps [12]. This also helpful to introduce steps to curb the destruction of soil.

m) Detection of crop nutrient deficiency: Farmers and other agricultural experts have also been supported by remote sensing technology to assess the extent of crop nutrient deficiency and to come up with solutions that would increase the amount of nutrients in crops, there by raising the overall crop yield.

n) Forecasting of crop yields: This can provide reliable estimates of expected crop yield during planting season using different crop details, such as crop quality, soil and crop moisture levels, and crop coverage. When all of this knowledge is integrated, crop yield is almost correctly measured.

o) Precision farming: Precision agriculture has resulted in the cultivation of safe crops that, over a given period of time, guarantee optimum harvests for farmers.

p) Crop intensification: It involves collecting essential crop data, trends, rotation needs, and diversity.

q) Flood mapping and monitoring: Farmers and agricultural experts may use remote sensing technology, imparted adequate knowledge, will prevent any potential catastrophe.

r) Satellite meteorology: For the generation of various items, different land, water management applications, and satellite derived rain fall products are commonly used.

s) Mapping of water resources: Over a given farm land that can be used for agriculture say supplies on remote sensing are sufficient.

t) Tracking of climate change: It is crucial for tracking and deciding where crops can be grown.

u) Compliance monitoring: Remote sensing is critical for agricultural experts and other farmers to keep ensuring, guarantee planting and harvesting crops.
v) Soil management practices: In deciding soil management practices based on data collected.
w) Air moisture estimation: Humidity of region determines the type of crops that are to be grown with in the region.
x) Land mapping: To chart different production on particular land soils for specific purposes, the mapping technology is used.

2. Geographic Information System (GIS); It is a system designed for all forms of spatial or geographical data to collect, store, modify, evaluate, manage and view. The GIS application is a tool that enables, queries, evaluates, easily described, and coordinated with its various systems, different kinds of projection systems are available. Layers are mixed, edited and built in order to perform the basic task in GIS. 'In order to understand relationships, patterns and trends, a Geographic Information System (GIS) helps us to visualize, query, analyze and interpret data [13].'

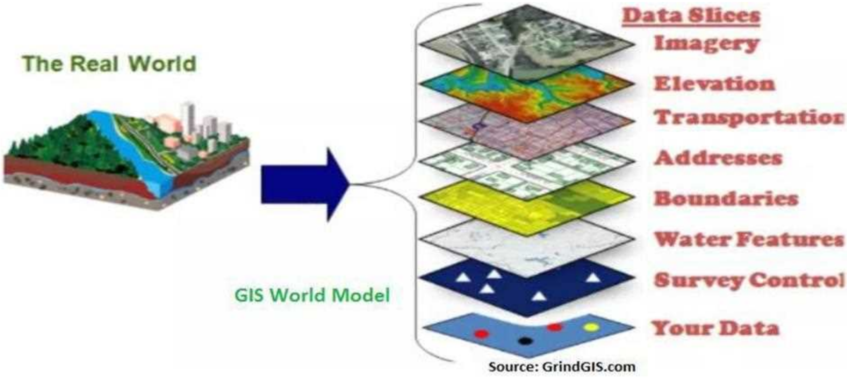

Figure 12. GIS and the agro-ecology.

GIS can be used to answer the question of location. The ability to merge various layers to view new information is the function of GIS. This tells from the map where the highlands are or where the best spot to build a house with a view of the river is. In order to find new knowledge, GIS also helps. The geographical data contained in the data bases will be shown in program map where layers are combined (*Visualization*).

GIS enables, generate, analyze, map, in a more generic sense. The science that utilizes geographical principles and structures is the geographical information system [14]. Combining soil determine suitable areas on location. Production might include land-ownership, transport, utilities, availability of labor, and distance from market centers. GIS use has the advantages of:

i. Better decision-making by individuals.
ii. Enhance data of people.
iii. Support and recognize neighborhoods where infrastructure is at risk or missing.
iv. Helps to recognize concerns around criminology.
v. Better natural resource management.
vi. Good coordination in an emergency.
vii. Due to better judgment, cost savings.
viii. Seeing various types of developments within the group.
ix. Planning for shifts in demography.

3. GPS for Agriculture Resources Mapping: GPS stands for Global Positioning System. In the recent past, this technology has progress impressively and has diverse applications throughout a range of industries. One of the key areas where GPS has found significance is guidance. Its applications not only useful for fishermen, officers and among others but extremely sophisticated applications are exceptionally effective and used in various industries [15].

Figure 13. GPS application in the farm field.

Farmers have a particular planting, weeding, and harvesting season and GPS enables them in different ways. The most significant agricultural uses of GPS are:

1. Soil profiling: Required data to determine soil variability accurately and to determine if a specific form of soil is suitable for a particular crop to grow. In soil profiling, soil sampling also helps to differentiate between soils that are viable and those that are not.
2. Weed location: Locate large land using linear sampling techniques. Weed typically hinders a crop's efficient growth and hampers subsequent yields over a given period of time.
3. Accurate planting: When preparing the planting of a given crop, GPS is also useful. Depending on the soil type, each seed has special spacing and depth necessary. Using GPS, in order to return maximum yields, it is easier to tell what spacing a given seed requires and at what depth the seed should be planted [16].
4. Determination of planting ratios: In deciding the planting ratios of seeds, GPS may also be used. Some seeds have unique spaces between them; where as those with other seeds may be planted.
5. Yield map formation: Production maps for particular crop types. For example, GPS can be used during harvesting to map the

expected yields of a given crop from one piece of land based on its characteristics.

6. Harvesting: In deciding how harvesting will takeplace, GPS plays an important role. An estimation of the size of the area being harvested and the expected returns the area will also be provided by the GPS.
7. Locating yield map: For gathering data, GPS is used to locate yield map.
8. Environmental control: The usage depends the ability of each squaremeter decreases the amount of pesticide used in the application. This helps the soil to consume all the chemicals, there by reducing the risk of run off.
9. Farm planning: Using different variables, such as soil characteristics and crop characteristics, GPS will provide the overall size of the field and help to decide what crop will be planted on what section of the farm land [17].
10. Land mapping: GPS offers an accurate estimation of the land being planned for agriculture. Through this, experts will be able to tell what portion of the field will be used for agricultural activities and which for other non-agricultural activities.
11. Soil sampling: Knowing what kind of soil is available on a given farm land is crucial, as this will help to decide the kind of crop to be planted on that farm.
12. Crops couting: Provides precise that helps for crops specific say existence form crops in location that thrive to improve.
13. Yield mapping: GPS can be used to estimate the yield of a given farm land by means of aerial mapping.
14. Correlation of crop yield production techniques: It determines the association with the crop yields over a given period of time to evaluate feasibility of a given method.
15. Soil property mapping: It allows researchers to determine what type of soil is in a farmland region ideal.
16. Machinery location: The exact location of such farm machinery can be identified by GPS.

17. Machinery direction: GPS isused to guide these to determine the direction in which the seeds are positioned.
18. Identification of area ssuitable for cultivation: To determine which areas are suitable for cultivation in a given region to assess the viability of the soil.
19. Classification of growing areas on the basis of different characteristics: It is possible to recognize and alienate areas that are not acceptable for cultivation, whereas that are suitable can then be established.
20. Evaluation of the availability of water in a given area: To determine availability of water or water sources in a region using GPS, bodies readily be identified.
21. Irrigated crop identification: GPS may also be used to identify areas where irrigated and non-irrigated crops occur. In order to help allow comparisons, this helps to build a profile between irrigated and non-irrigated crops.
22. Swamp and other water logged areas identification: Locate suitable crop to decide if certain types of land suitable or not.
23. Rivers mapping: To construct location that creates water flow. It is possible for farmers and researchers to recognize the existence of rivers and assist in deciding crops to grown.
24. Landuse in the locality: Used to track landuse in specific area.
25. Contour mapping: Assessing particular in situations where the land is irregular. This is because some crops in contoured lands will not do well, while others growing grow in these lands.
26. Mapping of irrigation systems such as dams or canals: This will make it convenient, as the requisite water is used to irrigate the land.
27. Meteorological mapping such as climate patterns: Mapping of certain climatic conditions in a given area.
28. Plantation mapping: GPS helps to construct plantation map to calculate crop yields.
29. Water bodies mapping: In order to determine region used to chart established water bodies within a given area.

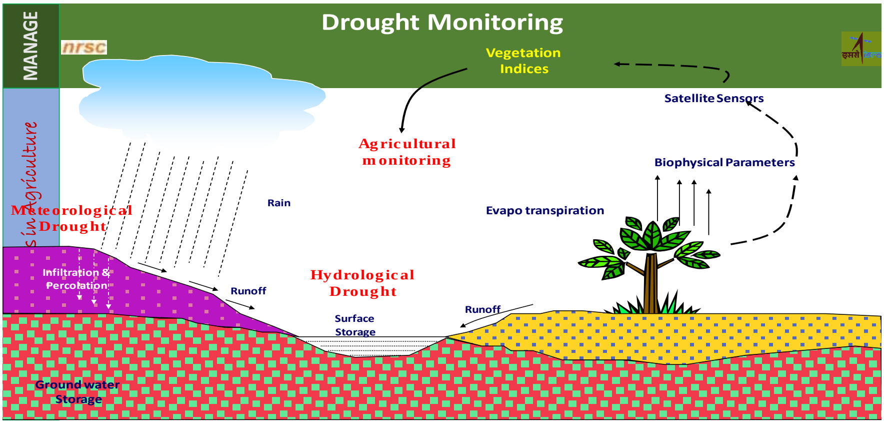

Figure 14. Drought monitoring.

Figure 15. Integrated hardware and software system.

In figure 15, crop offers an integrated hardware and software system for measuring soil moisture, temperature and electrical conductivity and sending that data to the cloud where it can be accessed from any mobile or fixed device.

SUMMARY AND CONCLUSION

IT resources have the ability to encourage, support the farming community in a variety of ways to be come an efficient and effective extension manager. ICT-enabled services are distribution to an external service provider of one or more processes based on specified and observable performance measures. The core ICT-enabled facilities and instruments have the potential, productive effect on farmers, rural citizens and the entire nation's agricultural economy.

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Chapter 10

IoT Based Data Collection and Data Analytics Decision Making for Precision Farming

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Abstract

This study presents a technique for solving the real time decision making difficulty of farming due to sudden changes in situation like atmospheric changes, monsoon, pest attacks, etc. if you talk about nourishing the world, the problem is even more severe and the reason can be related to Green Revolution problem. Agricultural scientists have been thinking about this problem for quite a while and the most promising approach right now seems to be that of data-driven farming. But there tend to be more styles to comprehend with all the IoT, therefore the Internet of Things will get interest from many more companies than simply farming. This study is focused on adapting the capability of IoT for data collection of features of crops and for automated decision making with data analytics algorithms.

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INTRODUCTION

World's food production needs to increase by 70% by 2050 to feed the growing population. The United Nations predicts that the earth's populace will achieve 9.7 billion by 2050 that may give foundation to international manufacturing that is an agricultural increase 69% by 2050. To meet the food production needs, agricultural businesses are embracing the Internet of Things for analytics and superior production competences (Viani 2017; Hedi 2017).

Know-how in agribusiness is absolutely nothing new. Manual techniques and tools had been the criteria more than 100 years ago, and then the Industrial Revolution had introduced to us with cotton gin (Veenadhari 2017; Rajalakshmi 2016). Precision agriculture as a technique given that the benefits are known was first proposed back in the 80s. It's been 30 years since then the technology hasn't taken off the biggest reason for giving revolution in farming. This technology hasn't taken off with its full potential because of the cost of existing data-driven agriculture.

Our goal is to bring down the cost of the data driven agriculture solutions by two orders of magnitude. In this chapter we talk about a few techniques that we think we can help us get there to the goal of World's food production needs of the year 2050.

Below, this chapter has outlined IoT applications in farming and how "Internet of Things farming" may help agriculturalists meet up with the world's food needs into the years which are coming (Srinivasulu 2017; Chavan 2014).

EXISTING TECHNOLOGICAL INTERVENTION IN AGRICULTURE

We want to take the technologies that we are building to the smallholder farmers everywhere in the world. For example, devices positioned in fields enable agriculturalists to get detailed maps of both the landscape and assets into the certain area, in addition to factors such as for instance acidity and heat for the soil (Krishna Jha 2017). They could additionally access weather predictions to calculate climate forecasts.

We have a lot of unused spectrum; megabits per second of unused capacity. At this point we are not only talking of connecting sensors, we could be connecting cameras, drones and tractors. We could be getting a lot of information that we previously couldn't get if we talk to any agricultural scientists. The number one problem we'll talk about is data. How do you get data from the middle of the farm? The above mentioned technologies can be used to run forecasts which can be statistical to their agriculture produces and livestock.

In a farm, what we want to get to are those kinds of maps where the soil moisture level six inches below the soil are collected and mentioned. Throughout the farm how do we get there? If you wanted to build an accurate map like this you need lots and lots of sensors. We will probably need a sensor every 10 meters. But, putting a sensor every 10 meters is expensive. So the key question is, can we build such a map using very few sensors. The way we solve this problem is using UAVs these are drones which can fly large areas very quickly. They have a camera at the bottom that that can take images of the entire farm.

If we follow these techniques it will help in making precision agriculture, the course of making use of satellite imagery as well as related technology (particularly tools) to detect and record information because of the objective of refining manufacturing productivity while reducing budget and resources that are preserving (Ferrández-Pastor 2018; Tech-Target 2017).

Smart greenhouses influence the IoT and associated products to produce a microclimate that is sovereign to crop manufacturing. These well planned surroundings prevent the brawls of bad climate and predators while producing the output in time that is acceptable to agriculturalists for finest effectiveness (Tech-Target 2017).

Farmers making use of greenhouse that is sensible observing schemes can take imminent information from big data and analytics to manage crop spraying, irrigation, lighting, temperature, moisture, and more.

The key technology we can use is using artificial intelligence and machine learning techniques. It is a way to use the aerial image to interpolate the data from a few sensors and predict what these values are in other parts of the farm, just to give you an idea the state of the art farming.

One would put a few sensors and then use either linear interpolation or Cragen's method. It is a state of the art but, just use that to do the prediction. With this technology we can use the image the key insight. That is if two parts of the farm looks similar either in RGB hyper spectral multispectral imagery, they're likely to have similar values. So this was one of the key algorithms that people were using.

The invention of block chain technology is giving its potential to the IoT that will make a difference within the agriculture sector because of its potential to offer businesses with significant records on produces. Sensors can used by farmers to assemble information regarding crops that will be recorded onto block chain, and consist of facets which are distinguishing well as salt and sugar content and pH level (Hedi 2017).

In some of the countries where we want to get aerial imagery and wanted to use a drone, we needed to get permission from the Ministry of Defense. At that point if it isn't happening so, then how do people get aerial imagery? People use tethered helium balloons which are tethered to the ground they fly up 250 and 200 feet and they are able to take continuous imagery of the farm. They can last up to four to seven days. The particular thing they built are a custom mount on which they put a Smartphone and a battery pack and this thing can keep clicking pictures for a really long period of time. People use this technology to monitor floods too. So, when there is a flood they need to throw away the entire crop. With this technology he can monitor he knows which crops had actually touched by the flood and only throws away those. Crops in places like Africa someone could just walk around with the balloon or put it on a bike or a tractor and we have computer vision algorithms based on which we can stitch this together to create these big aerial maps for the entire park. The key challenge here was that with drones we can keep them stable with balloons they'll move around with camera is not always facing down. So we have computer software based on which we are able to solve these problems. So going back how we build those accurate maps, we'll get the aerial image either from drones or from balloons. We then build these beautiful pictures of the entire farm we then take the raw sensor data and build the machine learning algorithm. the artificial intelligence of them that's a model of how would these variables propagate throughout the farm and then use that to predict what these values are throughout the entire farm. We can do this for pH moisture and temperature and scientists are working on other variables as well.

FARMING DATA COLLECTION WITH IOT

If we look at the startups in the modern agriculture a lot of them are working on either sensors or drones. People have been able to combine them in a meaningful way but we're just starting on the space there's a lot more to be done. But this seems like a very promising approach to build these maps at low costs with the IoT devices. We can bring down the cost of each sensor with technology. We need much fewer sensors than what we would otherwise need to build accurate maps like this. The challenge is how we can gather a lot of data and bring it to the farmer's house over the Smartphone. We apply machine learning. But the connectivity from the farmer's house to the cloud is not that great. Many farmers they pay for broadband, but all they get is one to three megabits per second connectivity in their house. Just to give an idea of how limiting that is if we fly a UAV a drone in 15 minutes. We could be generating over a gigabyte of data. We can't send that to the cloud over 1 to 3 megabits per second connection it will take a long time. The other challenge is this connectivity is also prone to outages (Shakoor 2017).

In farm incarnation we are able to show the farmer beautiful pictures of the soil map for further exploration of their farming potential. For instance, the metadata of the soil map to advice that we were able to flag that the top left corner of the farm is still moist that we have not explored yet. Also, after the farmer had applied lime we were able to flag that the dark parts that is still acidic. The key question here is how accurate is this so. With this study, we went to three farms each of three different five acre plots and we captured a thousand measurements. The values captured are of the farm beats technique of using aerial imagery with drone sensor data. So we have the results for temperature, pH and moisture. The used soil temperature would report temperature in one degree Fahrenheit and so on. So the key takeaway here is not that we are more or less accurate than the actual sensors themselves but that are our predictions are so close to the actual measurements. Also, they are actually actionable by the farmer. Through this kind of IoT based and drone based techniques we can gather a lot of data that didn't exist and applying the latest advances in artificial intelligence and machine learning we can bring actionable insights to the farmers.

Recent techniques, including IoT, carry enormous prospective to give potential push to the agricultural sector for higher production. The five ways that are mainly useful while employing IoT to boost agriculture include the following:

Better Regulation

IoT give a control over the agriculture that is internal, which reduces the related production dangers. It would provide a capability to calculate the yield output that can be helpful for planning a better crop distribution that is acceptable by farmers.

Cost Management and Spend Decrease

Iot based farming gives us a crop supervision assistance. This will reduce the probability of farm yield overproduction, therefore, dipping surplus. The capability to anticipate the gaps in farm development and cattle health assists to mitigate production that is dampened.

Data Management

Perhaps the farming sector has big data composed by agriculture IoTs, like climate conditions, mud eminence, crop development blueprint, and livestock wellness background. This data tracks a business's development, employee's performance, machinery efficiency, etc.

Increased Product Quality and Amount

The ultimate improvement of crop processes gives us a potential to handle the manufacturing that is entire and, at exactly the same time, guarantees improved farming quality with computerization practices.

Increased Business Efficiency

This effectiveness is because IoT has given way to the mechanization of a few processes. Utilizing smart products considering IoT, we could automate numerous agriculture operations, e.g., irrigation, fertilizing, or control that is pest (Prasad 2017).

According to most of the benefits stated earlier, it's understood that the introduction of IoT in farming is sooner or later ultimately causing greater income generation. The livestock sector in IoT can also be witnessing its advantages. A benefit of IoT in this area has arrived in wearable products that gather health-related data by checking the cattle's task every day. Another device utilizes IoT to examine this content that is fat of. All that given data is gathered and processed to take decisions concerning the wellness associated with the cattle.

With the use of IoT the agriculturalists can handle nursing their livestock's wellness. It's beneficial in avoiding the death that is undesired of pets. There are already IoT based devices in market like wearable smart watches and fit-bit bands, which are created to monitor the heartbeat, BP, health, etc. Through devices the dog owner is suggested about any danger to his pet. This kind of devices would also be useful for farmers, which will record and alerts the farmers about conditions associated with animal.

IoT devices are already in place to monitor weather conditions that will massively benefit in farming. IoT gives accuracy farming possibilities and already plays an important role in farming. The implemented sensor devices positioned inside and outside of the field gives climate that is real-time information. They assess this information to anticipate climate that is favorable facets like moisture, rainfall, and temperature. Such devices permit weather stations to automatically adjust climate conditions as per the particular pair of directions to produce smart greenhouses. The placed IoT will provide a timely information regarding greenhouse like temperature, illumination, moisture situation, and soil quality. As we discussed earlier the IoT based farming for greenhouses will minimize the budget, improve framing monitoring capability and will make the whole procedure cost-effective.

An important factor of agriculture supply chain is grain storage. If there is a technique to identify the conditions in a grain storage space container, then send information about fill levels, temperature and moisture in the storage facility to avoid spoilage or other dilemmas times which are numerous per day, it will be very useful. Thanks to the future engineering techniques, such devices are already in there the market. Insects are a definite challenge that is genuine farms. This risk calls for stable actions to overcome its effect that is undesirable on. IoT holds prospective that is great this respect, plus it allows the farmers to deal with numerous such challenges with more precision with the help of IoT-enabled sensors that is capable of detecting the damage caused by insects in real-time. AI algorithms also used for extracting such information analyzing the collected data with highest accuracy. This knowledge that is extra with an increase of accurate pesticide applications.

By 2050 we're going to need double the amount of food than what we have today. That's mainly because of two reasons. One the population of the world keeps on increasing it is going to be around 10 billion by 2050 and two because we have upward social mobility. So we're going to need more food per person. As we need more food the resources that we have to produce that food are shrinking. The amount of water that we have available is going down, the land that used for agriculture shrinking because cities and towns are expanding and taking of that space. While we shoot for that growth we also want to be mindful of our environment.

Agriculture as an industry is one of the biggest contributors of greenhouse gases. So we want to achieve this growth in a sustainable way. Clearly this is a big challenge for us as humanity. Much like the 70s when we had the first agricultural revolution we're looking for a disruption in the space. Fortunately for us there's been a lot of research on this topic from a lot of people in agriculture chemistry and physics. One of the most promising techniques today is something called data-driven agriculture.

When we talk about traditional farming we treat entire farm as one single unit. Data-driven agriculture says is that it's not the right way. To go about it instead what we should be doing is to map our farm. We need to create a map of our field that can show us the exact amount of moisture in each individual part. So for example this part is drier and this part is more weight. Then we want to treat them accordingly. So if a part is drier we want to give it more water. What research current currently has shown is that by doing that we can achieve improved yields, we can reduce our input costs and we can also improve sustainability. One of the biggest reasons data-driven farming is the high cost of data collection. If we're a farmer today and if we want to do data-driven agriculture we have two options. We can collect all this data manually. So we take a sensor plug it into the soil and measure a value. We walk a few steps, we do it again and we keep doing that for our entire field which can stretch miles. Clearly that's not feasible. The other option is to use really expensive sensors.

Farmbeats is an end-to-end IOT system for data-driven agriculture. It's a tool to enhance farmer and farm productivity and farmers have used for other applications beyond just data-driven farming. Farmbeats is an end-to-end system that can enable agricultural sensing at two orders of magnitude. We took an IoT that is fairly automatic. They can cover large areas quickly and they can give us visual feedback. We take this visual feedback and use it to extrapolate sensor information from a small number of sensors.

At high level so we take a drone. We send it over the farm to take a video then we compress that video into a high level panoramic overview of the farm. Then we combine it with this past deployment of sensors using tools from machine learning and computer vision to create precision maps. For creating moisture map we need a very small number of sensors. But we can interpolate these values using the visual features and by doing that we can extrapolate the value from a small number of senses over a large area. So now we are collecting all this data from cameras drones are moisture, temperature, pH, etc. how do we process this data and where does this processing happen.

One simple idea is to send all of this data to the cloud similar to Amazon Alexa or Google Home. Cloud will process this data. but the problem for farmers is that this connection from the home so this cloud is typically very weak so it is not always a broadband connection and even if this connection is strong enough it's very prone to outages so they can be thunderstorms, they can be floods and this network might be down for weeks. A solution to this problem was to use the PC that already exists in farmer's home or on farmer's office for regular accounting purposes and transform it into an intelligent edge. This edge device can combine all of the sensor data locally into small summaries that can be sent to the cloud. It can provide time-sensitive services to the farmer on the farm itself and the cloud. Then deliver long-term analytics or cross form Analytics depending on these summaries. So essentially there are all the sensors can interface with the Gateway using multiple technologies like TCP.

Then this gateway itself can run services locally which can be accessed on a web server offline. Then we can also do active component migration between the edge and the cloud depending on what type of communication we can enable.

About deployments we have drones and sensors on the field that can communicate to the steamy white space base station using Wi-Fi Bluetooth or Laura which can talk about over TV white spaces to the gateway where a lot of the services and brought of the processing happens. Then this gateway will come compress this data into summaries which are on the cloud. So the farmer can access data both on the cloud and on the local gateway. we have we measured the accuracy of the farm beats as opposed to the sensor we are measuring it against the least amount of the sensor for temperature pH and moisture.

THE PROPOSED METHOD

Accurate and ordered data collection is essential in effective data analysis and prediction. So data collection can be considered as a vital part in precision farming. If the planter is enforcing such correct and accurate data collection method with a must suitable device for data collection, it will help in the genuine boost in crop productivity. There a lot of researches already in place about precision farming. In (Amandeep 2017) clarify and give a good pattern about yield monitoring in the long run creates a GIS that is unique database helps planters to simply recognize yield inconsistency within an industry, to produce improved variable-rate choices, and produce an account of spatial industry information. Field monitoring has become a more profession job area. For instance IoT based farming is been adopted by many countries for grain plants and corn-soybean rotation systems. This technology may be extended to other crops too like potato, onion, sugar beet, tomato, hay, citrus, grape, and sugarcane. There are various components that will play vital role precision farming. The precision farming researches done for various crops like rice, watermelon, garlic, tomato, onion, mustard, cocoa, cashew, grape, tea, etc. have given promising results. The factors of precision farming like yield variability; yield diversity assessments, yield spoilt information, and industry effectiveness are to be tested for various climate situations of developing countries like India where the population is already 1.38 billion.

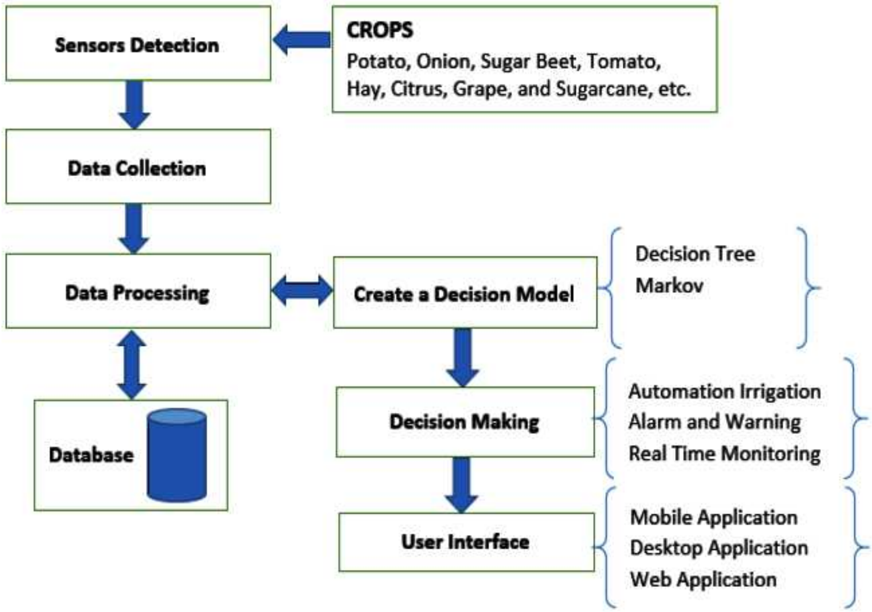

Figure 1. System Model of the study.

Soil planning is another important step in precision farming. Here the ultimate intention of the farmer would be to make a farm that is weed free and seedable for quick germination. A step significant in spoil planning is tilling, that is turning the soil and loosening it. This task needs much energy and incurs much input of energy source and cost. This may also incur the risk of soil erosion depends on the location of the farming site. Fortunately the precision farming equipment nowadays help the framers reducing the effort, energy and cost of farming without compromising the by enhancing the accuracy, effectiveness, and sustainability regarding the procedure. Such precision farming equipment would sense and input several information. Let us consider a scenario where the temperature radiation may be observed in a farm. Some crop may get harmed with high in atmospheric temperature. So there needs some airflow system to get control over the heat. It is known that varying temperature may catalyze difference development, germination, sprouting, flowering, and good fresh fruit development. The water vapor may be another factor influence these crops. For instance higher humidity may influence hydria push; shutting the stomata and will influence the photosynthesis that is depend on osmosis. The best water level required for crops are depend on the factors like it's kind, age, stage and environment. pH factor of water is also another influence the crops. Other factors are dampness contains, electric conductivity, the temp of dirt, etc. Moreover, the Light dependent resistor is really a photograph sensor (Khan 2018) that is conductive. According to Gaikwad S.V et al. (Gaikwad 2015), a sensor that is wireless (WSN) is definitely an infrastructure made up of sensing, computing and interaction elements that enable the administrator to monitor & get a handle on regarding the specified parameters within the system. WSN can be used for information collection, monitoring, surveillance & medical telemedicine. WSN is useful in irrigation system, Greenhouses for monitoring & controlling parameters like water flow, temperature, moisture, moisture, etc. The System Model adopted by this study for data collection of crops and decision making for advises to farmers is depicted in Figure 1. There were many kind of sensors you can use to get information that is neighborhood like heat sensor (e.g., DHT11), moisture sensor (e.g., HH10D), Soil sensor (e.g., SN-M114), Water-level sensor (pH measurement sensor), and Light Dependent Resistor. First, the method starts with sensors detection such as for example water degree, temperature, moisture, soil moisture, and light. The collected information from sensors will put into a database. This collected information would cater to the need of making a decision model which in turn helps in decision making. A decision model is part of AI algorithms that will help in machine learning and decision making. A decision model is based on decision tree that is hierarchical in nature. This decision tree follows a top to bottom approach. Each node of this tree is decision that separates each course through staying class. The decisions process would happen through continuous process by going down the tree till the leaf node. Based on this decision model, the system would alert the farmer about humidity and other discussed parameters which may affect/affected the crop for quick solution. This choice model will help farmers maximize their farming and profit by giving timely prediction.

AUTOMATED DECISION MAKING WITH DATA ANALYTICS

Three types of provision are required to bring together the elements of an IoT data analytics – the crop feature history, the infrastructure, which enables devices to do the analytics, the provision of content and a means of distribution (Nirmal Kumar 2011). Each of these may be provided to stakeholder as a whole or tailored to an analytics engine setting or need.

As mentioned above, the crop feature data history needs to be elicited to analytics setup, for instance a Hadoop infrastructure using a flume script. Apache flume is utilized here as an automated data collection tool, that is a a distributed, reliable, and available system for efficiently collecting, aggregating and moving large amounts of log data from various sources and to store it to data store like Hadoop.

Finding Popular Pest Data, for Instance 0x001 [African Bug]

for each word in the IoT/drone given data
quality = takeout(extract id, 0x001 text)
end
for each quality
count_id = addup (id€0x001 text)
end popular_hashrtext = max(count_id)

Pest Classification

```
While T in C do
while words in the IoT/drone given data do
if word = = any phrase in dictionary_pest then
word_rating = d_r;
continue;
end
end
avg_rating = avg(word_rating)
if avg_rating ≥ = 0.0 then
Provided pest is found positive
end
else if avg_rating < 0.0 then
Provided pest is found negative
end
else
Provided pest found is neutral (need further verification)
end
end
```

Pest Detection

A dictionary based method is used here for Pest analysis. For this a dictionary of pests is created with all known pests unfavorable for crops around the world. With this dictionary a tokenized words has been mapped. This is done to rate the tokenized words. The table of the dictionary contains id, word. We performed left outer join operation on a table. If the word matches with the pest word in the dictionary, then a ranking is given to the matched word or else NULL value is assigned. A hive table is created to store id, word and then rating.

CONCLUSION

This study observed that the IoT could be used to gather information that is neighborhood on accuracy farming. The farmer could easily get the information which can be real-time monitoring his field. The information that is regional is water level, heat, humidity, soil dampness, and light from the different crop (rice, watermelon, garlic, tomato, onion, mustard, cocoa, cashew, grape, tea, etc.). The machine learning structure and decision tree model proposed here is tested and found its results accurate for predicting pest destruction with 7% error rate. This model can be utilized by farmers for getting timely prediction of pest attacks in crops thereby improving production in area where the crops are prone for pest attacks in large.

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