DEVELOPMENT OF PRECISION CONTROLLED GREEN HOUSE MANAGEMENT SYSTEM USING MACHINE LEARNING ENABLED INTERNET OF THINGS

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Jan-2024

DECLARATION

I, hereby declare that the presented work in the thesis entitled **"DEVELOPMENT OF PRECISION CONTROLLED GREEN HOUSE MANAGEMENT SYSTEM USING MACHINE LEARNING ENABLED INTERNET OF THINGS"** in fulfilment of the degree of **Doctor of Philosophy (Ph. D.)** is outcome of research work carried out by me under the supervision of **Dr. Manwinder Singh**, working as Professor, in the **School of Electronics and Electrical Engineering of Lovely Professional University, Punjab, India**.

In keeping with the general practice of reporting scientific observations, due acknowledgements have been made whenever the work described here has been based on the findings of other investigators. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

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CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled **"DEVELOPMENT OF PRECISION CONTROLLED GREEN HOUSE MANAGEMENT SYSTEM USING MACHINE LEARNING ENABLED INTERNET OF THINGS"** submitted in fulfillment of the requirement for the reward of degree of **Doctor of Philosophy (Ph.D.)** in the School of Electronics and Electrical Engineering, is a research work carried out by **Ashay Rokade,** 41900712, is bonafide record of his original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.

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ABSTRACT

Currently, the existing wired system for smart farming, as it was difficult to manage and install, is replaced by wireless communication. Smart farming with precise greenhouse is installed to improvise in managing the growth of agriculture and therefore observing different environments in precision agriculture. A numerous system for agriculture developed for control system and remote monitoring control system of precision agriculture. But due to limited solutions, greenhouse monitoring is not yet competent to deal with agriculture growth on entirely control systems. Smart farming with accurate greenhouses needs to be implemented for better farming growth management, and therefore precision agriculture monitoring in various conditions is required. The Internet of Things (IoT) is a new era in computer communication that is gaining traction due to its vast range of applications in project development. The IoT provides individuals with smart and remote approaches, as an example, smart agriculture, smart environment, smart security, and smart cities. This is the most recent technology that is making things easier these days.

The IoT has fundamentally expanded remote-distance control and the diversity of networked things or devices, which is an intriguing element. The IoT comprises hardware as well as the internet connectivity to real-time application. Sensors, actuators, embedded systems, and an internet connection are the key components of the IoT. In the farming industry, the IoT is crucial to boosting utility. Innovative agricultural practices and medical informatics have the potential to increase crop yield while using the same amount of input. Individuals can benefit from the IoT in various ways.

Intelligent farms require the creation of an IoT based infrastructure based on sensors, actuators, embedded systems, and a network connection. The agriculture sector will gain new advantages from machine learning and IoT data analytics in terms of improving the quantity and quality to fulfil rising food demand. Fog computing is a developing computing approach to extend and assist cloud computing. Fog computing platforms have several characteristics that help provide services for the users in a reduced time and thus improve the QoS of IoT devices such as being close to edge users, being open platform, and its support for mobility. Thus, it is becoming a

necessary approach for user-centric IoT-based applications that involve real-time operations. The objectives of this research work are the following.

- To analyze various methods to develop a smart farming ecosystem under greenhouse environment.
- To develop an internet of things (IoT) based autonomous system for smart farming environment using smart sensors like moisture sensor, temperature sensor, soil sensor etc. for computational data analytics.
- To optimize proposed system using machine learning for fog layer enabled devices to achieve the precision management.
- To compare and analyze the proposed method with existing system with performance parameters like accuracy, latency, resources utilization and sensitivity.

As a result, an interest is developed in creating a smart farm IoT application. In greenhouse agriculture, this study presented remote sensing of parameters and control system. The objective is to manage CO_2, temperature, soil moisture, humidity, and light, with regulating actions for greenhouse windows/doors dependent on crops being carried out once a quarter throughout the year. The main goal is to properly regulate greenhouse conditions in accordance with plant requirements, to enhance output and provide organic farming. The results show that the greenhouse may be controlled remotely for CO_2, temperature, soil moisture, humidity, and light, resulting in improved management. In this experimentation, Gerbera and Broccoli are considered. The primary purpose is to adjust greenhouse conditions in line with plant needs in order to increase production and provide organic farming. Overall implementation is remotely monitored via IoT using Message Query Telemetry Transport (MQTT) on Adafruit IO Cloud Platform, and sensor data is analysed for its normal and anomaly behaviour.

The findings of greenhouse elements such as soil moisture, CO_2, temperature, and light for broccoli and gerbera plants are investigated using a graphical depiction based on real-world data collected by the suggested model. On Adafruit IO, the equipment is used to track of greenhouse elements from afar, including soil moisture,

CO_2, temperature, and light. Farmers may collect these data using an Adafruit IO cloud account and an Internet connection.

The four essential components of the proposed approach are the cloud layer, the fog layer, the edge layer, and the sensor layer. The data required from sensor layer for analytics model is collected by using an IoT-based embedded system device for two greenhouse plants with sensing parameters as input and related actuators as output. The two different analytics models are developed for intelligent and precise farming using the classification and regression model. The primary goal of this analysis is to enhance production and provide organic farming by adjusting farming conditions according to plant needs that are considered in the experimentation.

A precise control of sensing parameters, CO_2, soil moisture, temperature, humidity, and light intensity in a smart greenhouse agriculture system is presented using a regression-based supervised machine learning approach. However, it appears that the greenhouse could be operated remotely for CO_2, soil moisture, temperature, humidity, and light, resulting in improved management. The overall implementation is remotely monitored through IoT using MQTT, and sensor data is analysed for its normal and anomalous behaviour. For effective computation over the cloud layer, analytics and decision-making system has been developed at the fog layer and constructed using supervised machine learning algorithms for precise management using regression modelling methods. The proposed framework has improved its presentation and now allows it to properly achieve the goal of the entire system.

Finally, an analytics and decision-making system was built at the fog layer, employing two supervised classification-based machine learning approaches, using support vector machine (SVM) and artificial neural network (ANN) for effective computation over the cloud layer. The experimental results are evaluated and analysed in MATLAB software with statistics and machine learning toolbox. The performance evaluation of proposed system is analysed using confusion matrix-based parameters, accuracy, sensitivity, specificity, and f-score for classification based supervised analytics, root mean square value for regression-based supervised analytics with computation time for training and testing phase of model.

It is found that the classification accuracy using SVM is much better than that of ANN and other state of art methods. The suggested approach is also successful in creating smart agricultural systems with intelligent prediction-based decision support. On the basis of the experimental results, the proposed strategy also proved to be the most effective in providing actuators with predictions and control. Furthermore, this proposed model can be used in a real-world scenario by making it robust and weatherproof.

Keywords: *Precision Agriculture, Intelligent greenhouse, Internet of Things, Machine Learning, Smart Farming, Fog Computing.*

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High achievement always takes place in the framework of high expectations. It has been rightly said that every successful individual knows that his achievement depends on a community of people working together. However, the satisfaction that accompany the successful completion of any task would be incomplete without the mention of the people who made it possible. The expectation was there and I began with a determined resolve and put in a lot of hard work.

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ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
APPA	Adaptive Plant Propagation Algorithm
CNN	Convolutional Neural Network
CO_2	Carbon Di Oxide
CPS	Cyber Physical System
EC	Electrical Conductivity
FA	Fitness Averaged
FLC	Fuzzy Logic Controller
FN	Fog Node
FNR	False Negative Rate
FPR	False Positive Rate
GAN	Generative Adversarial Network
GPS	Global Positioning System
GUI	Graphical User Interface
HN	Home Node
ICT	Information and Communication Technology
IDE	Integrated Development Environment
IIoT	Industrial Internet of Things
IoT	Internet of Things
MAP	Mean Average Precision

MAS	Multi Agent System
MLP	Multilayer Perceptron
ML	Machine Learning
MQTT	Message Queuing Telemetry Transport
NDVI	Normalized Difference Vegetation Index
NPV	Negative Predictive Value
ORP	Oxidation Reduction Potential
PCGMS	Precision Controlled Greenhouse Management System
PPV	Positive Predictive Value
QoS	Quality of Service
ROA	Rider Optimization Algorithm
ROC	Receiver Operating Characteristics
SFSDA	Smart Farming System for Data Analytics
SVM	Support Vector Machine
TDS	Total Dissolved Solids
UAV	Unmanned Aerial Vehicle
VI	Vegetation Index
WCS	Wireless Communication System
WSN	Wireless Sensor Network

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CHAPTER 1 INTRODUCTION

1.1 OVERVIEW AND BACKGROUND

The land and quality of the plants are now the crucial daily bounds for money harvests or food crops, making plant agriculture a creative task. Poor farming knowledge and information about new techniques is a significant problem in modern agriculture. Our forefathers in the agricultural sector avoided using specialised technology for individual plant growth in favour of general natural phenomena. The introduction of technical machinery into the agricultural sector has made it possible to cultivate plants in settings that go well beyond the norm. This has led to the production of higher yields and lower manure usage. The huge use of fertilisers, defoliants, and water in plant crops is in line with their natural rationality [2, 3]. In intensive nursery settings, growers often use agrochemicals in quantities that exceed the true yield demands, leading to ecological pollution and waste. Crops are handled with a lot of induction without taking target estimates obtained as a result of advanced crop-checking technology into account, and when compared to overall creation estimates, the value of water and agronomics is inexpensive. In particular, a sizable percentage of working people relies on the farming sector for their livelihood. In India, this number is particularly high, with 53 percent of the working population and 61% of the working population, respectively [4]. When considering the size of its market, India is the second largest producer of organic goods in the world. By 2022, it is expected that farm revenue in India will have doubled, according to current studies and forecasts [5]. By 2025, Inc42 projects that the Indian agricultural sector would grow to a value of $ 24 billion. The sixth largest food and grocery market in the world is in India, where 70% of sales are made through retail. According to the first advance estimates for FY23 (Kharif alone), the nation's overall production of food grains is predicted to be 149.92 million tonnes. India's rapid population growth is the primary force behind the industry's growth. This is further supported by the increase in income levels in rural and urban areas, which has increased the demand for agricultural products throughout the country. Accordingly, the market is being encouraged by the increasing use of innovative technologies such as blockchain, artificial intelligence (AI), geographic information systems (GIS), drones, and remote sensing technologies, as well as the introduction of numerous e-farming applications.

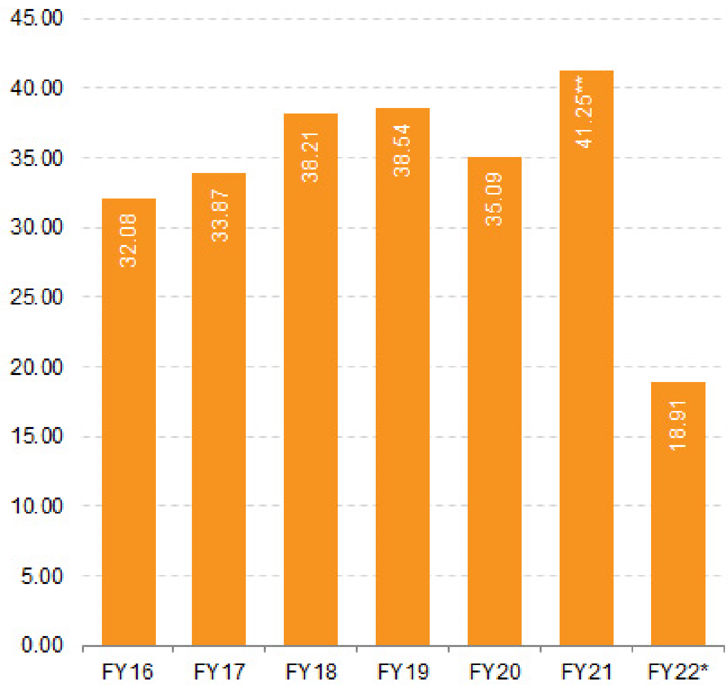

Figure 1.1 Agriculture Exports from India (US$ Billion) (Source: IBEF)

As shown in figure 1.1 the industry has had strong growth in terms of exports during the past 12 months.

- Exports of marine items totaled $7.77 billion in FY22.
- The value of rice exports (including basmati and nonbasmati) was $6.98 billion USD.
- Buffalo meat totaled $3.30 billion dollars.
- The value of sugar exports was $4.60 billion USD.
- The value of tea exports was US$750.93 million.
- The value of coffee exports was $1,020.80 billion USD.

1.1.1 Technological Progress in Modern Agriculture

Modern farming and horticultural production systems are undergoing significant technological progress, which has led to the terms "agriculture 4.0" and "Smart Agriculture" (SA) [6]. Numerous innovative technologies, such as autonomous agricultural trucks, satellite infrastructure, and unmanned aerial vehicles (UAVs), will be linked to future scenarios. In particular, modern farmers will benefit greatly from adopting both technologies related to precise farming and IoT. In reality, a much more sensible and superior horticultural production framework is needed to adequately address some impending problems, such as the rapid increase in population, atmospheric conditions, and the consumption of common assets. Therefore, investigations and mechanical advancement can be solutions to reduce these challenges. The new advancement in agriculture [7–10] is probably the one for the first half of the 21st century, with enormous design challenges frequently spiking enormous arrangements through challenging inventions. The advancement related to agriculture 5.0 is based on the concept that farms are using automated activities and emotionally supporting networks based on the freedom of individual choice, as outlined by the precision agriculture standards. As a result, it is likely that the ideas behind agriculture 5.0 will incorporate the usage of robotics and possibly even some types of artificial intelligence. Ranches have typically relied on a large number of sporadic professionals to gather harvests and keep profits high.

Since society has changed from an agricultural culture in which many people lived on homesteads to one in which many people lived in urban settlements, ranches are facing the difficulty of a manpower shortage. AI-enhanced farming robots are one approach to the workforce crisis. An example of how AI-enhanced farming robots can help alleviate labour shortage is a smart greenhouse management system. Smart greenhouse systems provide advanced energy optimisation and microclimate regulation [11-15]. The factors; temperature, humidity, light, and soil moisture are crucial to controlling and monitoring to ensure optimal plant growth.

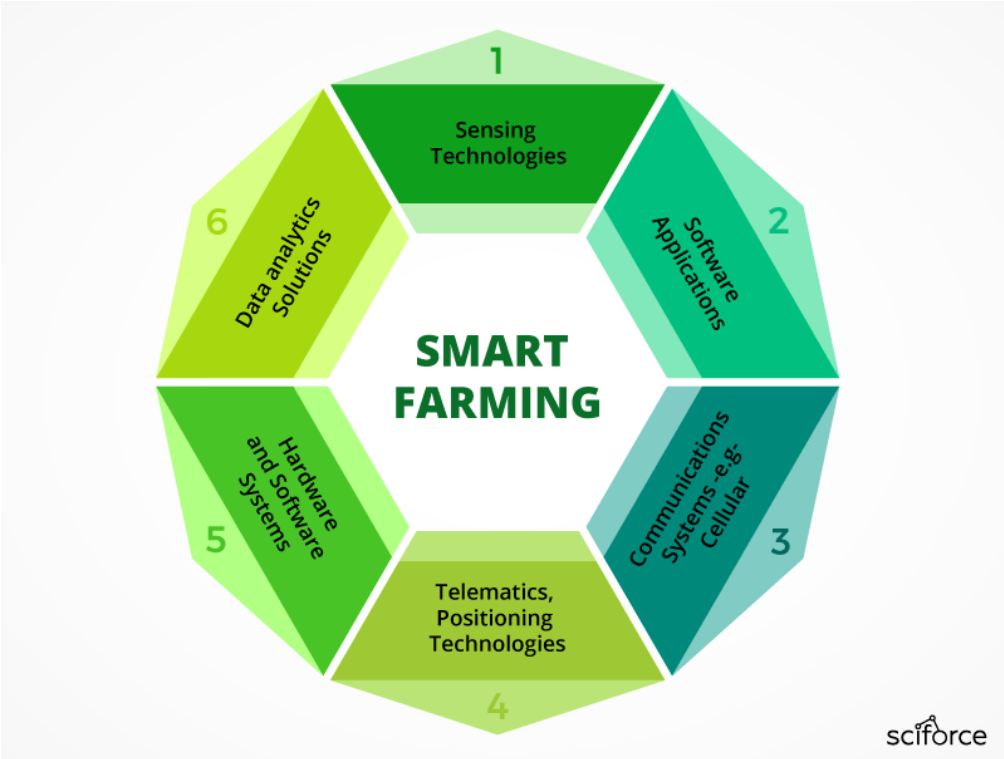

Figure 1.2 Smart Technologies for Agriculture

Figure 1.2 shows the smart technologies that will be beneficial for smart farming. Sensors for things like humidity, light, soil, temperature, water, etc. are all part of the field of sensing technologies. A farm may employ a software programme developed specifically for it. It is possible to communicate efficiently using a cellular system. Positional technology such as GPS or satellite may be used to construct machine learning (ML) algorithms for data analysis and decision making. [16, 18, 21-25]. Ecologists are interested in testing for the following criteria to better understand the plant growth cycle and to conduct active studies if any of the elements are changed:

- CO_2 level.
- Lycopene monitoring to determine the change of the produce.
- Nitrogen monitoring to determine the puffiness of the produce.
- pH Value.
- Phosphorous deficit to determine soil fertility.

There is a significant change in the way farms collect and use information to make informed operational choices. Information and communication technology (ICT) demand in agriculture, including machine intelligence algorithms and rationalisation of raw material use as a capital-centred system, cutting-edge electronics in beverage production in sustainable and environmentally sensitive practices, all add up to what is known as ‘intelligent culture’. New technologies are enhancing the lives of a wide variety of individuals all over the world. People's ability to influence their surroundings with more certainty is greatly facilitated by the IoT and other various forms of sample, such as grown samples and sample learning techniques. In order to provide essential information to the final labourer and services regarding the foundation and properties of agro production and structures, IoT and data reasoning are used in the environmental and agronomic sectors for two-pronged diagnostics and control of brilliant culture arrangements. The summary of smart agricultural aspects [31-34] is shown in Figure 1.3.

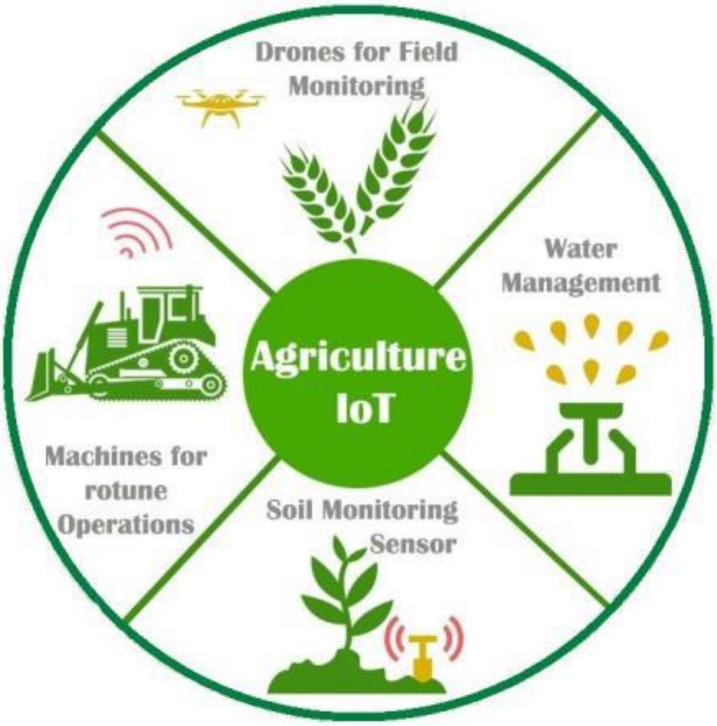

Figure 1.3 Overview of IoT in Agriculture

Actuators' intelligence is being controlled via ML. The algorithm takes into account the specific environmental and soil parameters of the plant to provide the best possible recommendations to the farmer. IoT is also used to gather sensor data from the field so that the data and ideas from the ML algorithm are made available on a UI platform, making it easier to monitor the field in real time. Predictions are made using sensor data using supervised machine intelligence algorithms, and agricultural solutions are provided. The use of IoT gadgets provides an automated data prediction. The data collected will help the farmer make a well-informed choice [96, 97]. The technology suggested will improve the effectiveness of the system and foresee more advanced intelligence-based control possibilities. Climate change will reduce crop yields because it slows plant development in agricultural settings. Greenhouse gases, temperature, soil moisture, and light are just some of the environmental sensor elements that require constant maintenance and monitoring. Intelligent agriculture could use IoT innovation as a solution to this problem [98, 99]. For optimal plant development, this type of agriculture carefully controls greenhouse variables such as temperature, water flow, and light management. AI-enhanced farming robots might help alleviate the labour crisis. Smart greenhouse systems provide advanced energy optimisation and microclimate regulation. The following factors - temperature, humidity, light, and soil moisture - are crucial to controlling and monitoring to ensure optimal plant growth.

There are main keywords on which work focus, which are explained below.

1.1.2 Greenhouse

A greenhouse is a structure similar to the state of a home that is protected with the essential elements to preserve microclimate, such as water stream management, directed temperature range, etc. for robust plant development. As a result, it stays away from things like too much light invasion, high temperatures, diseases, creepy crawlies, etc. Any plant may be grown by a farmer at any time of year by preserving the greenhouse environment. As one of our topics of interest, greenhouse farming has relevance that shows the reality of why it has gained so much significance [104–108].

1. Greenhouses need much less water systems than ordinary cultivars, as it traps the dampness.
2. Reduces the span of editing and expands the nature of harvests as well.
3. Successfully adjusting environmental conditions like humidity and temperature to meet the needs of plants.
4. Through nurseries, it is also possible to develop slow-time-of-year crops.
5. Pests are easily controlled.
6. It is exceptionally flexible, as the harvests can be filled in different climatic conditions.

Figure 1.4 Schematic of Green House Technology

The term "greenhouse technology" refers to the practise of using automation to provide optimal growing conditions for plants or crops. Although its main function is to shield crops from unfavourable weather, as time has progressed, its use has expanded to include additional benefits, such as higher yields and lower input costs. Greenhouses are simple to regulate because they feature a closed environment. The latest technology available to commercial plants allows maximum yield with minimal effort [109–112].

The state-of-the-art smart greenhouse integrates cutting-edge scientific knowledge from a variety of software and hardware technologies.

i. Greenhouse Controllers

By automating many greenhouse management tasks, environmental controllers help farmers increase production while decreasing overhead. Using a smartphone app, you can open and close vents and turn on and off using a smart motor controller. Sensors placed throughout the greenhouse send data to controllers, which are then programmed to meet certain specified requirements. Sensing is where we must begin.

ii. Sensors

Sensors in a greenhouse record data on various factors such as the interior and exterior atmosphere, surrounding CO_2 levels, light intensity, photoperiod, water potential, and electrical conductivity, allowing the grow room controller to maintain optimal conditions for plant growth. By using an app to keep tabs on the myriad of factors that go into greenhouse maintenance, you may save a lot of time and money on labour. The sensor reports crop-level information to the operating system, which then prompts the motors to open or close. Let us take a look at how automation ties everything together.

iii. Automation

Automation helps farmers boost crop yields by maintaining a constant growing environment while cutting costs by reducing energy use and man hours. This is great news since it frees up producers' time and effort for other endeavours, like growing their business or collaborating with other companies. The IoT provides a solid answer through sensor-triggered automation.

iv. Data

The greenhouse controllers collect and analyse data over time, revealing which settings for watering, feeding, lighting, and climate management result in the best harvests. This information can be used to improve yields, resource efficiency, and bottom lines in repeated harvests.

The various advantages of greenhouse farming are addressed in the following sections [113-119]. The discussion about increased production, minimising production risks, profit maximisation, etc. are discussed.

i. Increased Production

By simulating natural conditions indoors and producing more plants per square foot than you could in an open field, greenhouse farming can increase agricultural productivity.

ii. Minimising Production Risks

When crops are contained in one area, they are protected from such rapid temperature changes. In addition, it can prevent birds and other animals from damaging crops by keeping them at bay.

iii. Profit Maximisation

Combining greenhouse farming with other techniques, such as hydroponics, has been shown to increase yields by two to thrice compare to open-field agriculture. Profits can increase if efforts to save energy and materials are successful.

iv. Controlling Pests and Illness

Pests and diseases are less likely to be a concern if a greenhouse is used. Only the necessary workers need access to the enclosed area, reducing the likelihood that pests or diseases may spread to the crops through human contact. If any issues arise, you may also pinpoint them with this method. Separating sick or damaged plants from healthy ones can save the harvest.

v. Perpetual Harvesting

The regulated environment of a greenhouse makes it possible to grow plants outside of their traditional growth seasons. High-quality crops can be cultivated year-round, regardless of the weather outside, thanks to greenhouse temperature control technology.

vi. Strengthened Safety and Stability

The greenhouse-controlled atmosphere is safe and stable for plants and workers due to the lack of interference from the outside world.

A greenhouse is a great method to cultivate plants, but it requires constant attention. Greenhouses cannot maximise crop yield without greenhouse environment and growth management systems. Greenhouse management can benefit from automation in administration or technology development. The care of plants that grow within a greenhouse requires management to adjust and regulate environmental factors. There are a variety of methods to supply plants with their daily needs, such as food and water [120–128]. Among these methods are:

a) Fertigation Equipment for a Greenhouse

An automated system for controlling irrigation systems, a fertigation manager is run by a computer. The state-of-the-art technology included allows the daily management of several irrigation schemes for numerous greenhouse crops based on greenhouse temperature, moisture, and more. In addition, it facilitates the accurate administration of plant hormones.

b) Water Purification for Hydroponics

Water treatment systems may be used to recycle and treat water, which is the best approach to supply clean water to your greenhouse plants. Modern ozone systems help filter irrigation wastewater into usable water to minimise water stress and maximise plant growth in greenhouses.

c) Managers of the Climate in Greenhouses

Greenhouses require a reliable climate and growth management system to control the inside temperature and humidity and to keep tabs on the exterior wind, rain, the sun and the air temperature. Keep tabs on the greenhouse's CO_2 levels, lights, shades, vent placement, and more.

The need for growth management and control systems increases as greenhouse plant cultivation expands. They offer assistance at every stage, from limiting fertilisers and sugars to stopping stem growth to ensuring adequate sunlight for optimal plant development and keeping an eye on the greenhouse lights. Everything in greenhouses must be meticulously monitored and maintained, from plant density to water content. A greenhouse management and control system uses cutting-edge technology to provide a unified platform to manage and adjusting all aspects of a greenhouse from a single location. The most effective greenhouse management systems can help with a wide variety of tasks, including but not limited to: heating, ventilation, irrigation, fertigation, carbon dioxide, humidity, shade, misting, water treatment and recycling, soil and moisture levels, and more. Such fully or partially automated solutions allow for more efficient greenhouse management on a larger scale. Without a reliable tracking and management system, dealing with issues and prioritising your work can consume a lot of time. Controlling all components of the greenhouse growth environment from one central location is possible with greenhouse automation [129–135].

The use of natural resources, such as light, heat, humidity, ventilation, and CO_2, is essential for healthy crop growth, with strong stems and roots and sufficient yields. Different types of climate have distinct effects on the production of various crops. The climate in the greenhouse must be managed to ensure uniform growth and high-quality harvest. There are five factors that can be adjusted to modify the greenhouse's climate. This makes it possible for plants of all types to flourish within greenhouses year-round, regardless of the weather outside. The following are the five environmental elements that need to be managed in the greenhouse.

a) Heat

To maintain the ideal air temperatures within the greenhouse, plant producers must carefully regulate the heating system. Some plants can suffer from heat stress or illness if the temperature is too high, while others will thrive if you create conditions similar to those seen in the summer.

b) Humidity

Humidity in the air has a significant impact on plant development. Air temperature, precipitation, and drought conditions are all potential causes of dampness. The plants inside a greenhouse produce heat and humidity by exhaling carbon dioxide and absorbing oxygen. Therefore, environmental management is crucial for optimal plant growth and harvest.

c) Air Circulation

Humidity can be reduced, temperature can be stabilised, and a new supply of carbon dioxide can be ensured all with proper ventilation. Therefore, plant life requires an open setting. But the appropriate breeze is essential for development. Fans and vents allow for the regulation of airflow within greenhouses.

d) Radiance

When tending crops in open fields, producers have little say over the intensity of the sun's rays. However, within greenhouses, the intensity of the light may be controlled. Different plants respond differently to different levels of light. For plants to thrive on a low-light diet, you will want to use light filters, blackout curtains, etc.

e) Carbon Dioxide

Carbon dioxide (CO_2) is another crucial environmental element that can have a significant impact on plant development. For photosynthesis, plants must absorb carbon dioxide, as you know. Gas boosts agricultural output in the same way. The ability to produce oxygen during photosynthesis can be stimulated by increasing the concentration of CO2 in a greenhouse.

Since growing greens in a greenhouse is an expensive venture, it makes sense to focus on growing high-yielding crops that have great economic value and sustained market demand. Greenhouses are typically used for the commercial cultivation of tomatoes and other crops that require a warm environment. Flowers, plants, fruits, and even transplants may all benefit from growing in a greenhouse. They can also be used to cultivate exotic greenhouse varieties. The economic viability of a greenhouse is influenced by demand, supply, weather, and labour. Common plants grown in Greenhouses for Flowers and vegetables. Our aim was to conduct our experiments with two plants: gerberas and broccoli [136-142].

The market value, vase life, and popularity of gerberas all contribute to the importance of the flower. Greenhouses in tropical and subtropical regions allow the cultivation of high-quality gerbera. The Gerbera plantation in the greenhouse is shown in Figure 1.5. Gerbera is a miniature perennial herb (about 30-45 cm in height) with hair on its body. The width of the leaves is about 3 inches. The stems are tall and lean, without leaves, and can be either a single hue or a combination of many. In warm and humid climates, it blooms continuously throughout the year. From seed to bloom, expect about three months. Gerberas can be grown from their own seeds, via cuttings of buds-containing clumps, or by tissue culture. Tissue-cultured seedlings are the best option for commercial growth in a controlled setting. Gerbera daisies have a rather lengthy vase life, making them ideal for use in decorative arrangements, occasional gardening, and even cosmetics.

Broccoli, the green crown gem vegetable, is a model food due to its abundance of beneficial properties. Fibre, iron, magnesium, potassium, zinc, vitamins C and B, and vitamins K are all present in abundance in broccoli. The sulforaphane chemical it contains is also cancer-fighting. These verdant trinkets are planted in early spring or late summer because they are cold-season veggies.

Figure 1.5 Gerbera flower plantation in Greenhouse

The broccoli flower plantation in the greenhouse is shown in Figure 1.6. A cold frame greenhouse, because of its structure, is ideal for growing broccoli and other cool-season vegetables. Planting it can result in one or two major harvests and several smaller harvests during the growing season. About two months before the final freeze date, plant broccoli seeds in modular trays. A greenhouse location with 6 to 8 hours of sunshine each day is ideal. Full light is ideal for growing broccoli; shade will result in a weaker crop.

Figure 1.6 Broccoli flower plantation in Greenhouse

1.1.3 Benefits of Smart Greenhouses

Smart greenhouse allows growers to minimise labour and improve efficiency in the use of resources and chemicals while maximising the yields shown in Figure 1.7.

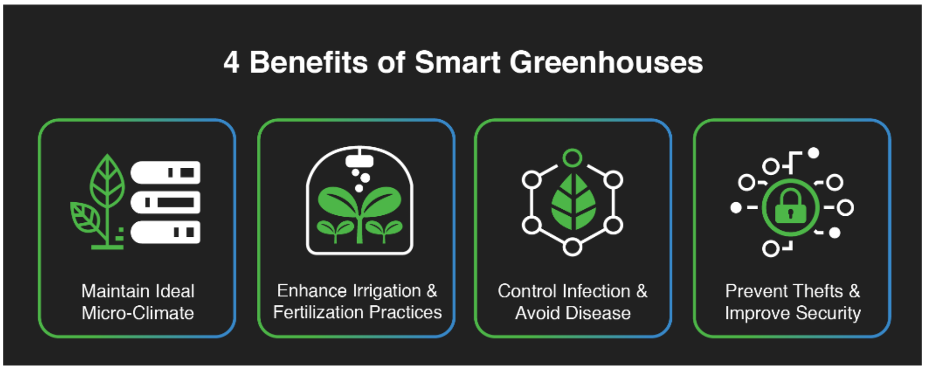

Figure 1.7 Benefits of Smart Greenhouse

i. *Preserve Optimal Microclimate Conditions*

With the help of IoT sensors, farmers can gather a wealth of information at a level of detail never before possible. They monitor the greenhouse's environment parameters in real time, such as inside and outside atmosphere, in terms of temperature, moistness, light intensity, and CO_2 levels. Keeping ideal environmental conditions for plant growth while promoting energy savings, this information triggers pertinent modifications to the HVAC and lighting settings. At the same time, motion/acceleration sensors may detect whether a door has been left open accidentally.

ii. *Optimise Water Use and Fertiliser Application*

Smart greenhouses help farmers monitor their crops and their environment simultaneously. This guarantees that the water and nutrient demands are met in a way that maximises harvests. Indicators of agricultural water stress include measurements of soil volumetric water content. Fertiliser needs can also be learnt from soil salinity tests. This information allows automatic activation of sprinkler and spraying systems to meet the needs of the crop in real time with as little human intervention as possible.

iii. Prevent the Spread of Disease by Eliminating Infection

Crop infectious diseases are a constant problem for farmers and significantly reduce profits with each new epidemic. Agrochemical treatments are readily available, but farmers are not always sure when to use them. Too frequent applications pose environmental, safety, and financial problems, while not using treatments might lead to harmful disease outbreaks. Insights into pest and fungal disease threats can be gleaned from samples from greenhouse conditions, external elements, and loam composition using an ML framework. Using these samples, farmers can minimise the cost of chemicals while still ensuring a healthy harvest.

iv. Reduce Crime and Boost Safety

The theft of high-value crops from greenhouses is common. Many growers do not have a reliable security system because it is too expensive to set up a network of closed-circuit television cameras. The affordable monitoring of the status of the doors and the detection of suspicious actions is now possible thanks to IoT sensors in smart greenhouses. They are connected to an automatic alarm system that activates right away in the event of a safety threat to the plant.

1.1.4 Precision Agriculture

Management systems focussing on precision agriculture are constantly evolving. They provide farmers with a wide range of solutions to common issues. However, precision agriculture encompasses a vast set of resources that farmers must understand to maximise yields. Precision farming uses cutting-edge tools like satellite images and field mapping to boost yields and profits. As an added bonus, it uses traditional materials to the fullest. Therefore, by making it easier to solve urgent economic and ecological challenges, this form of agricultural management promotes the development of sustainable agriculture. [143-155] Some examples of the technology used in such a system are satellite imaging, GPS, and drones. From this information, farmers learn about their crops, weather forecasts, environmental changes, and more. The ability to handle different pieces of land separately from each other distinguishes precision farming from conventional farming. Rearranging the quantity of fertiliser, optimising the movement of techniques, and conserving fuel are just a few examples of how zoning may help with field management.

i. Importance of Precision Agriculture

Precision agricultural technology allows farmers to manage their operations from a distance. Large fields or clusters of tiny areas are not a problem for even the smallest farms.

It significantly improves crop efficiency, reducing expenses while boosting output. Given that precision agricultural technology appears pricey at first appearance, that latter point is crucial. Compared to the savings made through more traditional farming methods, the long-term savings are much greater. As a result, farmers can determine the precise amount of fertiliser required and the best types for a particular region. Furthermore, precision farming technologies improve long-term planning of agricultural operations, allowing for quick changes in strategy in response to unforeseen events. The quality is maintained and a reliable food supply is made possible through efficient use of the land. As a result, precision agriculture in agriculture is crucial to ending hunger in the world.

ii. Benefits of Precision Agriculture

Both farmers and Mother Nature benefit from precision agriculture. Furthermore, these regions are linked because agricultural conditions are negatively impacted by environmental deterioration. Several advantages for such greenhouse management are as follows:

- Developing favourable attitudes.
- Spreading modern farming techniques to increase output quality, quantity, and minimise costs.
- Efficient use of water resources.
- Lowering the dependence on weather conditions.
- Preserving soil health by using fewer pesticides.

- Reducing the price of resources and things like water, seeds, gasoline, etc.
- The full genetic potential of the crops being produced is realised.
- Prevents soil degradation.
- The socioeconomic situation of farmers is shifting because of precision farming.
- Reduction of chemical application in crop production.
- To increase agricultural productivity.

With the use of precision farming, farmers can greatly raise the quality of their output while also cutting costs.

Limitations of Precision Agriculture

- High cost.
- Heterogeneity of cropping systems and market imperfections.
- Less technical knowledge, technology, and expertise can damage the crop.
- Can be easily applicable for large land holdings.

1.1.5 Internet of Things

The Internet of Things (IoT) is made up of intricate networks connecting billions of devices and people to create multistage, multishow, and multi-innovation systems. The condition of the smart environment can be created with the aid of equipment gadgets and web connectivity, providing information on cities, businesses, health, energy, transportation, and other aspects of our daily lives. This is possible by simply connecting all devices at any time and location with the input of information.

IoT refers to an arrangement in which various physical items, such as computers, servers, and mobile devices, are embedded. Smart homes and cities, transport systems, and healthcare networks are some of the most well-known uses of the Internet of Things. All of these structures have many moving parts. The advent of edge computing technologies has made the transition away from the traditional cloud-centric architecture. The uniformity of IoT's growth and architectures depends on the standardisation of their classification. There are four distinct levels in total: "service," "platform," "network," and "device." In contrast, most IoT gadgets aren't particularly powerful when it comes to things like central processing unit speed, amount of storage space, or battery life. This means that they are vulnerable to a wide range of cyber threats and should be treated as such [156-164]. Consequently, there are concerns about inadequate security and the potential for privacy violations. The blockchain is among the most promising new technologies that have emerged to deal with the decentralisation problems. In Figure 1.8, X shows the year and Y shows the connected devices in billions. Statistics project that the number of IoT devices will more than double in 2020 to more than 25 billion in 2030.

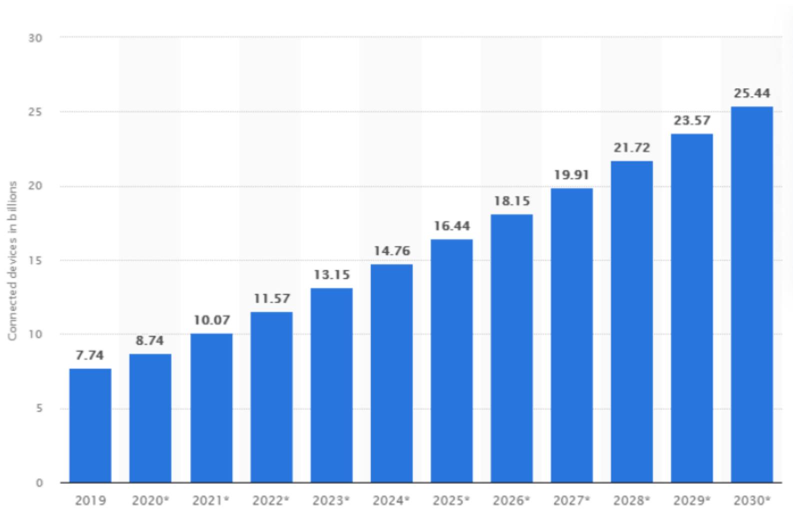

Figure 1.8 Expected IoT connection with coming generations

i. Components associated with IoT

An Internet of Things (IoT) system is a network that connects various gadgets, digital machines, and other objects that may transport data across a network without involving a human. We need to properly integrate five key elements, as indicated in Figure 1.9, for our system to be categorised as an IoT system.

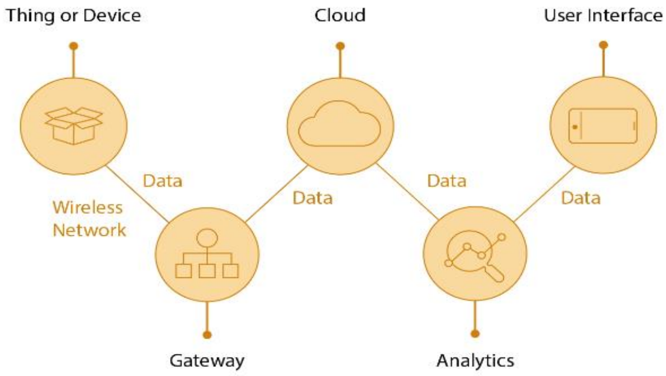

Figure 1.9 Primary components of IoT

ii. ***Things or Devices***

These have sensors and actuators built right in. While sensors take in information from their surroundings and send it to a gateway, actuators really do something with that information.

iii. ***Gateway***

The sensors send their data to the Gateway, where it undergoes preliminary processing. Provides protection for the network and the information being sent.

iv. ***Cloud***

Once gathered, the data is stored in the cloud. To put it simply, a cloud is a group of servers that are always connected to the Internet.

v. ***Analytics***

After the data are uploaded to the cloud, processing may begin. In this context, several algorithms are used for data analysis (including ML and similar methods).

vi. ***User interface***

The part of a computer system with which a user interacts to see or alter data.

1.1.5.1 Layer Architectures of IoT

The Perception Layer, Network Layer, and Application Layer are the three levels that make up the basic IoT architecture, which is illustrated in Figure 1.10 below. The first figure shows the basic IoT architecture with three layers perception, network and the application layer and second figure shows its advanced version with more dedicated layers in which a further business layer is added for application development in the business era and the processing and transport layer are added, where the transport layer acts as network layer and the processing layer acts as the intermediate data processing layer instead at the application layer.

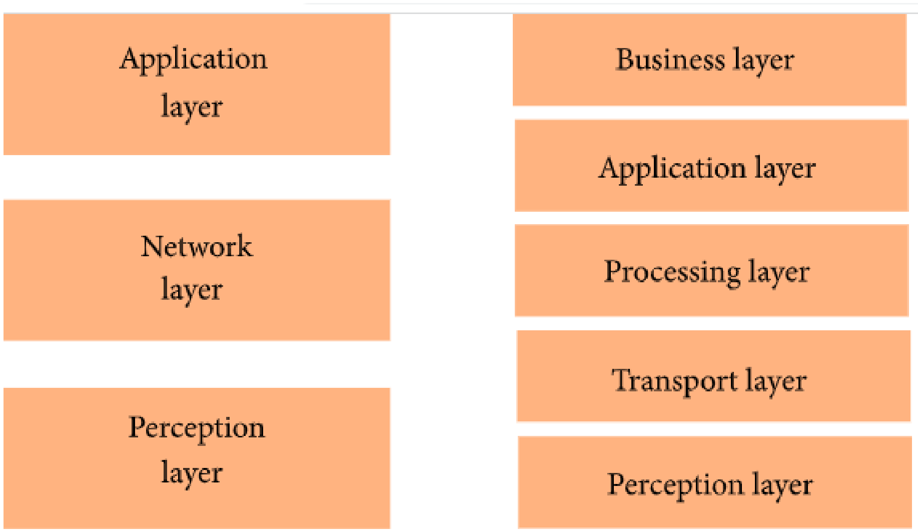

Figure 1.10 Layer-wise architecture for IoT

1.1.5.2 IoT based Smart Farming Cycle

Information is the lifeblood of IoT technologies. Smart farms, in order to operate at peak efficiency, need to establish a never-ending loop of data collection, analysis, and action [165-170]. An intelligent agricultural cycle may look like this:

- **Actions:** Operation of the tasks causes a recurrence from the beginning of the cycle.
- **Decisions:** The study results in options that farmers can use to improve their harvests
- **Diagnosis:** IoT solutions built in the cloud are used to analyse sensor data.
- **Observation:** Data about environmental parameters are collected using sensors.

1.1.5.3 Benefits of smart farming: How is the IoT shaping agriculture?

In many ways, agriculture stands to benefit from technological advancements and the Internet of Things. There are specifically 5 applications of IoT that benefit agriculture:

- The information, a lot of information, collected by smart agricultural sensors on things like weather, soil quality, crop growth progress, and livestock health. You may monitor the overall health of your company, employee productivity, machinery use, etc. with the information gathered here.
- Increased control over operations internally, leading to less danger in production. Knowing how much you can expect to produce helps with logistics planning. The exact amount of crops harvested may be planned to avoid having unsold inventory.
- Better cost management and less waste due to tighter manufacturing oversight. You may reduce the likelihood of losing your harvest by keeping an eye out for any abnormalities in the development of your crops or the health of your livestock.
- Automation of formerly manual procedures has led to an increase in productivity. Many steps in the production cycle, such as watering, fertilising, and pest control, can be automated with the help of smart devices.
- Increased production and better quality. Using automated systems to optimise yields and quality control throughout the manufacturing cycle.

1.1.5.4 IoT use cases in Smart Agriculture

i. Climate Conditions

The agricultural industry is highly dependent on the weather. And having faulty climatic knowledge severely reduces both agricultural yield and quality. But IoT technologies let you check the forecast live. Sensors are used to take greenhouse and atmospheric readings to determine which plant varieties would thrive under certain weather conditions. Sensors that describe the IoT ecosystem can precisely measure variables like humidity, rainfall, temperature, and more in real time. You can find a wide variety of sensors on the market to monitor all of these factors and set them up in a way that suits the needs of intelligent greenhouse farming. To promote optimal growth, these sensors monitor the environment and crops. If unstable weather is detected, a warning is sent. Having a physical presence during unfavourable weather is no longer necessary, which increases production and allows farmers to enjoy greater advantages of agriculture [171-178].

ii. Precision Farming

One of the most well-known uses of the IoT in agriculture is precision agriculture and agriculture. Using applications used for intelligent agriculture, we can track creature, vehicle, with field observation, and stock roster monitoring improves farming's precision and control. In PF, the collected sample is analysed with the intention of taking action. With the use of sensors, data can be generated in precision farming, allowing farmers to analyse the data and make timely, informed decisions. The adoption of various PF techniques for irrigation, livestock, vehicles, and other things related to farming, may significantly increase the production and efficacy of farms. In order to maximise productivity, precision farming analyses soil conditions and other relevant characteristics. Water and nutrient levels can be monitored in real time, and you can also monitor the operating characteristics of the linked devices.

iii. Smart Greenhouse

Weather stations can now automatically alter the greenhouse's environment using the Internet of Things based on user's instructions. Elimination of human error resulted in reduced costs and improved precision in greenhouses that have used IoT. The use of natural power sensors for greenhouses results in cutting-edge and budget-friendly farming. These kinds of sensor collect and send sample in real time, allowing for precise monitoring of the greenhouse environment. The sensors allow for remote monitoring of the greenhouse's water usage and condition through the use of email and text message notifications. IoT allows precise watering systems with pressure, humidity, temperature, and luminosity sample data gathering with the use of these sensors.

iv. Data Analytics

The established database system cannot handle the sample data that the IoT sensors have gathered. The problem can be resolved with an end-to-end IoT platform and cloud-based data storage. These systems have the potential to significantly improve the standard of daily tasks. Sensors are the primary mechanism for obtaining enormous volumes of data in the Internet of Things. Analytics tools are used to examine the data and get insight from it. Data analytics is useful to assess the state of crops, animals, and other agricultural factors. Better choices can be made with the data help of the obtained thanks to advances in technology. By collecting data from sensors, IoT devices allow you to monitor crop health in real time. Better harvesting decisions can be made with the use of predictive analytics. By analysing trends, farmers can prepare for expected weather and agricultural harvests. With the use of IoT, farmers have been able to increase both the quantity and quality of their production by better monitoring crop health and soil fertility.

v. Agricultural Drones

The deployment of agricultural drones is the most recent technological disruption that has significantly impacted agriculture. Drones, both ground-based and airborne, are put to work in fields for purposes such as crop analysis, monitoring, planting, and spraying. Drone technology has provided a significant boost to the agriculture business with the help of strategic management that works on real time data samples. A well-designed drone can pinpoint exactly where watering needs to be adjusted. As soon as the plant begins to form, the sensors report its status and compute a vegetation index. In the end, environmentally friendly drones have become the norm. The end effect will drastically decrease the amount of chemicals mixed with water.

vi. Smart Irrigation on Agriculture Land

Smart irrigation uses automated sprinkler systems and smart pumps. Sensors that measure soil moisture are becoming common, especially in agricultural settings.

Soil moisture sensors send data to smart pumps or smart sprinklers, which then activate or deactivate accordingly.

vii. Monitoring Soil Quality

To determine the fertility and moisture content of their soil, most farmers rely on a sampling procedure. Chemical breakdown differs from place to place, therefore, fortunately, this sampling does not provide reliable data. This is not going to help much in the meantime. It is crucial in agriculture because of this issue. To capture precise soil data that can be utilised in the dashboard or mobile app for farm monitoring, sensors can be placed at regular intervals throughout the farmland.

viii. Livestock Monitoring

Cattle tracking, animal welfare, and health monitoring are all areas where IoT devices could prove invaluable. This information can then be utilised to single out unwell animals for isolation, reducing the risk of disease transmission. Labour costs can be reduced by using Internet of Things-based sensors for livestock monitoring.

1.1.6 Machine Learning

ML enables a broad idea with many useful applications, including contemporary agriculture. ML has the potential to revolutionise agriculture by helping farmers select quality and health before planting. Artificial intelligence (AI) includes the subfield known as machine learning. In many ways, predictive analytics may be a game changer. Artificial intelligence allows farmers to collect and handle data much more quickly and efficiently. AI can assist farmers with many activities, such as evaluating market demand, forecasting prices, and determining the best times to sow and harvest [179–185].

ML has several uses in agriculture. Here are some of the more crucial ones:

- Suitable time for crops
- Crop Yield Patterns
- Water and Irrigation

- Agribots
- Farm animals

There are many uses of ML in Precision Agriculture which are mentioned below

- Analyze Market Demand
- Risk Management
- Breeding Seeds
- Crop Protection
- Soil Health Monitoring
- Harvesting

Many problems, including climate change, lack of irrigation systems, food shortages, low groundwater levels, large losses, and waste, have plagued the agricultural industry in recent years. The future of farming may depend on cognitive solutions such as ML. A significant scope is in terms of broad-scale agricultural research and development, but there are many applications and cutting-edge technological instruments available that may improve the system as a whole. The potential for ML in agriculture is immense. For this reason, stable and secure apps are required. Extremely powerful ML tools can adapt to changing environmental conditions. It also helps them make decisions in the moment and provides the right infrastructure to gather contextual information. The high cost of cognitive solutions is an additional issue that can be detrimental in agriculture. To find the best solutions and enable the wider distribution of technological tools, technology is used [186–192].

The study of data, including ML, is becoming increasingly popular. Algorithms are taught to classify data, generate predictions, and find hidden insights in data mining projects using statistical approaches. These discoveries inform application and commercial decisions that should eventually have an effect on vital growth indicators. Data scientists are projected to be in increased demand in tandem with the development and proliferation of big data. A branch of artificial intelligence known as machine learning (ML) enables computers to "learn" new skills and improve over time without being explicitly programmed. In the discipline of machine learning, the goal is to develop methods that can autonomously access sample data and learn from them. Various data samples, observations, examples, experience, or instruction, are the basics for ML. It examines the data for patterns so it can make inferences from the provided examples. The fundamental objective is to empower network nodes to learn and adapt on their own, without the help of humans [193-205]. There is little doubt about the usefulness of ML for AI systems. However, what ML strategy should you implement? Among the numerous options available for ML training are:

- Supervised learning
- Unsupervised learning
- Semi-supervised learning

1.2 RESEARCH PROBLEM

Conventional agribusiness, which depends only on farmer's insight, indicated unequipped for taking care of the rapidly developing horticultural prerequisites. Additionally, present day horticulture, which actually transfers generally on manual human intercession, shows numerous restrictions, particularly with regard to continuous upkeep, where a convenient right intervention can set aside a ton of cash, and ideal wrong reaction can be expensive. The endless manual endeavours demonstrated illogical and not generally conceivable, particularly with regard to checking the ecological conditions [14] [17] [35]. As an example, nurseries enable the entertainment of the uncomfortable ideal boundaries that plants need to improve creation or mimic the natural states of specific geological territories to locally obtain goods that are typically imported.

New farming patterns also attempt to manage crops in controlled environments. Striking control of temperature, humidity, and illumination can also be used to maintain a strategic distance from the major climate variations that influence crop production. Today, horticulture targets expanding crop yield as far as creation and quality. Agriculture has developed directly as a result of the growing population. Improving ranch productivity and cultivating quality without constant manual inspection to meet the world's expanding food demand is the fundamental test for agriculture businesses.

Environmental change is also a difficult model in agribusiness. The most surprising test in quality cultivation is climate's eccentrics' (e.g., erratic precipitation and temperature, etc.) and the states of the climate (eg, soil dampness) [2] [9].

When managing decisions aimed at increasing harvest production or water consumption, rural researchers and decision-makers take the clouded boundaries between such lexical standards as established in specialised writing into serious consideration. Furthermore, a significant number of rates used to decide water or compost depend on general guidelines, which once in a while are obtained from long periods of involvement in specific yields on specific conditions [21] [28]. This makes troublesome not exclusively to look at or test the presentation of any proposed strategy for water system or preparation in heterogeneous conditions, yet in addition make the errands of checking and dynamic. Keeping in mind that the dependable estimation of factors identified with crop development and yield is not new nor costly any longer thanks to the Internet, very few conceptual models are as yet accessible that may fill in as brisk choice apparatuses for clients.

Today, research has been done on remote sensor networks used in farms and greenhouses, demonstrating the prospective method of using IoT capabilities to complete dynamic cloud formation [33] [37]. This has sparked the development of a comprehensive implanted architecture on a realistic scale, incorporating IoT capabilities that are general enough for a variety of anticipated uses. To serve as an example of how such a framework might be useful in the fight against the harmful effects of environmental change.

There are, however, some circumstances in which a solution that consists of a single IoT layer that sends data straight to a cloud layer may have flaws. While some studies and solutions simply focus on the Cloud, others use cloudlet- or fog-based approaches. Thus, Edge computing has developed to reduce the costs related to moving, storing, and processing data in the cloud [12, 13]. Only the useful data are delivered to the cloud after being filtered and pre-handled at the organisation's edge with the aid of an Edge layer in an IoT environment. This helps customers achieve faster response times while preserving the framework's capabilities in the event of communication disruptions between the IoT layer and the cloud [25], [29].

1.3 MOTIVATION AND SIGNIFICANCE OF RESEARCH

1.3.1 MOTIVATION FOR PRESENT RESEARCH

As I belong to a farmer's family and have grown up observing the huge changes in the field especially in my region i.e. Vidarbha region in Maharashtra. I found that farmers are not ready to accept the technological changes and their importance in agriculture. The basic requirements for any farmer are land, air, nutrients, water, and sunlight. With this, any farmer with their hard work and knowledge about the crop can make a good profit in agriculture. But degradation of soil due to chemically active fertilizers, drastic change in the weather, less technical knowledge of the crop, uneven atmosphere, etc. are many reasons that lead farmers to huge loss in agriculture.

The price of the crop or any agricultural product is highly dependent upon the geographical area. The agricultural crop or product is less expensive in the area where it is developed. Crop cultivation is also depends on the geographical atmosphere. It becomes very difficult to cultivate crop under unfavourable atmospheric conditions. Which ultimately leads to an increase in the price of product due to transportation and packing cost.

Research is carried out to overcome these boundaries and develop a smart greenhouse system in which the farmer can take production of any crop without worrying about the atmospheric conditions and nutrition requirements of the plants. By using a proposed system farmer will be able to monitor the crop without even physically visiting the field.

As the global population increases, every country will have challenges in providing for its people's nutritional needs. Everyone can have decreasing natural resources, shrinking productive land, and more uneven weather patterns. In response to these challenges, the agricultural industry is adopting ‘smart agriculture’, which uses the IoT and big data technology to enrich productivity. The Internet of Things (IoT) consists of a wide variety of innovative technologies and solutions.

To increase efficiency and longevity, the agricultural industry must rely more and more on data and information. As a result of advancements in ICT, information collection, information storage, sample data analysis, and sample data use in agriculture are increasing day by day. The usage of blockchain technology also allows for the recording of a plant's entire history, from the origin of its seed to its final destination after harvest. Supply chain transparency can be improved and illegal and unethical manufacturing can be minimised with the use of this information.

To make farmers rich with more profit and less production rate, an innovative smart farming system is introduced in the research. Smart farms are designed to improve the quality of agricultural production while minimising human involvement. You might, for instance, keep an eye on a number of things while you are away from your farm and take appropriate action. Smart farming allows you to make informed decisions while technology takes care of the task.

1.4 OBJECTIVES

1. To analyze various methods to develop a smart farming ecosystem under greenhouse environment.
2. To develop an internet of things (IoT) based autonomous system for smart farming environment using smart sensors like moisture sensor, temperature sensor, and soil sensor etc. for computational data analytics.
3. To optimize proposed system using machine learning for fog layer enabled devices to achieve the precision management.
4. To compare and analyze the proposed method with existing system with performance parameters like accuracy, latency, resources utilization and sensitivity.

1.5 CONTRIBUTIONS

The main contributions of the research are as follows.

- The research provides a detailed study of the existing smart greenhouse systems which allow the research gap findings to be taken into account and provide unique and efficient solutions to the problems highlighted in the research study.
- The research provides a four-layer framework for IoT-based farming system which can make it easier to establish an intelligent low-cost agricultural system.
- The research creates effective analytics and decision-making models that can be employed with supervised ML for precise and intelligent farming, which helps farmers to get high productivity at low cost.
- Farmers can cultivate any plant in any region without worrying about the atmospheric conditions.
- It is not necessary for farmers to take the knowledge about the crop and technical aspects of greenhouse management because research does it for them.

1.6 THESIS ORGANIZATION

This thesis consists of the following six chapters.

Chapter 1 entitled "Introduction" is the introductory chapter. This chapter explains the background and motivation. It also describes the research goal to be reached and the scope of work that will guide the research. Also, describes the importance of the fundamentals of proposed system keyword technology with its architecture and various features and significance related to domain.

Chapter 2 entitled "Review of Literature", contains a review of the literature on the theme related to this research. In this chapter, we present a literature review of existing work on IoT based monitoring system and intelligence smart farming with various ML approaches.

Chapter 3 is entitled “Development of IoT based Smart Farming System”. This chapter gives an explanation of proposed layer architecture with working flow. Also, the proposed approach that has IoT based on IoT for smart farming system is presented.

Chapter 4 entitled “Analytics and Decision-Making Model Using ML for Precision Management”, presents the proposed methodological layer wise data flow which mainly consist of analytical and decision-making model which is implemented using multiple supervised regression ML algorithms is used for precise management.

Chapter 5 entitled “Experimental Results and Discussion”. Based on the simulations, multiple classification methods are compared in accordance with the various performance parameters primarily based on confusion matrix and analyse the proposed system performance with state of the art methods.

Chapter 6 entitled “Conclusion and Scope for Future Research Work”, emphasizes the main accomplishments and utility of the research and also discusses the scope for the development of future research work which could be applicable for designing of secured intelligent farming systems.

CHAPTER 2 LITERATURE REVIEW

2.1 REVIEW OF LITERATURE

This chapter discusses the many contributions to the field of "smart farming" made by researchers who took into account different methods of crop production and the incorporation of technology into the system.

2.1.1 Smart Farming Based on IoT Methods

A soilless culture ready to respond to the demands of full distribution nurseries using tolerably salty water was proposed by A. Santa et al. [1]. It is constructed on top of low-effort hardware and is supported by open-source software at the neighbourhood, edge, and cloud levels. Cyberphysical systems (CPSs) collect data and carry out continuous nuclear control actions by interfacing with agricultural devices at the neighbourhood level. To strengthen system dependability against network access failures, the platform's edge plane is in charge of handling and monitoring basic Precision Agriculture (PA) functions close to the entry organisation. Finally, the cloud platform uses information examination modules in a FIWARE architecture to compile historical and current data.

A. Chehri et al. [2] focused on how distant sensors are essential to the structure of the smart farm, allowing for the management of a significant amount of data produced intermittently or continuously to study it draw conclusions from it, and construct a cutting-edge computerised smart farm. They did this by employing multitier rationale planning and organisation calculations to solve the problem of a weak business network and the detection of random inclusion in the Internet of Things.

A highly adjustable perceptual framework offered to control and monitoring nursery temperature using IoT technology [3]. The principal function is to monitor the weather and regulate the temperature inside to save energy waste and maintain optimal working conditions. The nursery's weather is monitored using a Petri Nets (PN) model, and the resulting reference temperature is then transmitted to a temperature-guidance block. The next goal is to provide an adaptable energy efficiency (EE) framework plan that manages massive measurements of the huge IoT huge data captured from sensors using a unique chart information model to assess and predict production, crop growth rate, energy use, and other connected difficulties.

Choukpalli et al. [5] combined with a cloud-based social hub develop a biological system that characterises sensors and the relationships between different chemicals. Information on shared assets, part cultivates, and community collaborations is stored in the cloud, and part ranch and centre ontologies are developed to track these interactions.

El-Basioni et al. [6] refer to the IoT standardisation, the agricultural industry has an IoT reference engineering. For success, the suggested Agricultural IoT Reference Architecture (AITRA) needs to take a close look at the IoT ecosystems and the application area. In the article, the three tiers of AITRA are illustrated: Device, Cloud, and Business, together with their corresponding structures, demonstrations, basic organisational structures, applications, and services.

An Internet-connected Home Node (HN) and a mobile app designed for iOS smartphones [14] are the final pieces of this holistic dynamic, which reorganises data representation and plant health monitoring. The proposed IoT framework has been tested for more than seven days in a real world setting (a vegetable nursery). The data gathered identified potential sources of an infection that affects vegetables (in this example, the end root), validating the VegIoT Garden.

J. Ruan et al. [15] conducted a study of the state of opinion on the topic of agricultural IoT literature over the past decade by analysing data from 3168 publications and the 100,205 references they cite in Web of Science. Combining resources from many research and scholarly grounds reveals emerging trends in applied IoT methods, as well as issues of worry in farming. Collaboration organisations identify exceptional countries, foundations, and artists based on their contributions. In addition, convincing studies and researchers are shown, displaying ongoing research and development in the horticulture IoT. They also make suggestions for the future based on the results of the survey, such as improving the farming IoT frameworks, implementing information security and sharing, implementing sustainable energy arrangements, conducting financial research and managing activities related to the IoT of horticulture, and using IoT for financing and e-commerce for agriculture fields.

Saiz-Rubio et al. [16] review each important development, from the acquisition of crop field data through the use of variable rate applications. It examines the state of modern ranch management frameworks and helps farmers in making better decisions to reduce costs, protect the environment, and better coordinate food production in light of the anticipated increase in the global population.

When the recommended arrangement to current IoT-based gardening and growth arrangements, network idleness decreases [17]. Here, a solution offered for detecting and compelling is based on cross-layer channel access and direction. They look at how the group is structured based on factors such as participation levels, activity levels, and sleepiness. The main focus of this article, which offers a control system based on the Internet of Things, is the expansion of agriculture and agriculture in provincial regions. Controlled system components and enhancements are discussed and researched from many angles, including test bed evaluation, improved energy efficiency, delayed execution, and throughput, all results of the MAC and guiding response for the IoT. When the suggested arrangement is used with the WiLD group, latency may be reduced and throughput for the final mile of the network can be increased. The suggested haze-setting structure saves the company time and resources by reducing the need for costly data transfers.

Focussing on the need for people to keep a close eye on their growing crops, the investigation focusses [22] on the foundation and design of an IoT-enabled agriculture. When interacting with customers, a company maintains control across several domains and continuously collects data. The configuration allows the person in charge to concentrate on other duties while the system watches the harvest. It is clearly set up on non-agricultural grounds such as residential and business holdings. To promote optimal crop growth, the framework will control environmental factors such as temperature, light, relative humidity, and fixation in the water. The group is in agreement that this will advance agriculture and allow people to buy vertical farming equipment for their homes without having to worry about relying completely on farmers.

AgriTalk [24] is a cheap IoT platform for accurate soil cultivation. They run growth tests on the turmeric plant and the results show that overall quality of turmeric is improved using AgriTalk. More than ten times as much curcumin is packed into every 100 grammes of this supplement than is found in similar products on the market today. They demonstrate how to effectively maintain AgriTalk for precision farming by demonstrating how to intuitively create the linkages between the sensors and the actuators with the optimal cultivation knowledge. To study the delays in AgriTalk's IoT messages, they employ estimates, explanatory examination, and recreation studies. Our research shows that AgriTalk can easily respond to rapid and dynamic differences in field climate conditions in soil development and that delays for programmed control and programmed manual control exchange with significant distances (over 30 Km) are short (under 0.2 seconds).

It is recommended [27] to construct a structure that offers a framework to fence off a greenhouse, a chicken coop and a fish tank. They can monitor and adjust the temperature with a raspberry pi. The IoT is highly dependent on sensors and actuators for climate monitoring and response. Using this structure, we can deduce causal relationships between climatic factors and recycle the loss from one environment to the next. The primary function is to make climate control far more effective. The next step is to pinpoint the situations where the dependence on waste is most pronounced. The final objective is to provide a framework that may be easily expanded for use in any agricultural setting.

The SWAMP project, for example, Brilliant Water Management Platform for Precision Irrigation, was announced by Kamienski et al. [32]. It develops Internet of Things-based strategies for smart water across the board in a precise water system, and is being piloted in Italy, Spain, and Brazil. They discussed the SWAMP perspective, the project's engineering, the pilots, and the situation-based progress measure. Although still in its infancy, Marsh has recently attracted the interest of ranchers, agribusiness organisations, and government agencies around the world. At this point, they have gone to the pilots, researched them, and investigated the ideas based on the individual pilots' ends, gains, and needs. The most important lessons learnt so far hint to the consistent characteristics and variable highlights of pilots that can significantly bolster the blueprint for a really reproducible SWAMP stage.

The Internet of Things (IoT) precision farming framework [34] consists of a group of gadgets that calculate more than 14 boundaries in the soil, during harvest, and the surrounding environment. They have combined the system with our cutting-edge farming platform that is cloud-based and offers a configurable interface for gathering data from various sensors and providing the farm manager with useful insights. So far, the system has been used to assess the viability of two green crops, cabbage and capsicum, during the Rabi (winter) period of 2017. They include our interactions with the project and lessons learnt from the season-long programme that led to a 20% reduction in agri-input costs and a 10% increase in output.

A smart cultivating arrangement [35] can collect data from the field environment for continuous analysis to improve crop discernibility and overall yield. It can also design and implement a brilliant innovation for the horticultural sector that does not compromise on environmental or rural sustainability. The suggested framework's core is comprised of natural limitations including crop temperature, ambient stickiness, soil moisture, and light intensity. In conclusion, they also evaluate the presentation and efficiency of the MQTT convention in different stacking scenarios.

The suggested investigation [36] is based on the blueprint of a typical IoT system designed to increase agricultural production by strategically arranging water resources and preparing for harvests according to their specific needs, environmental factors, and climatic projections. In this paper, a framework for a modest water system and its planning are proposed. Manure can be applied to the soil in a lawful manner using the suggested treatment framework. As a result, you will need less compost, which will save your money and boost soil quality. A versatile and user-friendly software has been created to help provide this information to the ranchers in their local language. The cultivation of bean stew was subjected to context analysis, which was judged to be acceptable as a nonexclusive structure.

A solar-powered intelligent farming monitoring framework is provided that makes use of IoT devices [37]. The goal of these solar-powered data collection nodes was to send field data to a central location for analysis and planning. Two models were examined to separate people's preferences for how they would like their energy-collecting devices to work. A proof-of-concept for the framework's functionality is introduced, and a trial test bed is used to demonstrate this. Results of preliminary research suggest that charging and powering a device with the help of an energy collection device can extend its useful life.

S. Sarangi et al. [38] have developed a practical edge stage that incorporates a flexible and adjustable sensor hub, allowing us to locally handle the rancher's logically significant detecting needs. Our edge platform, along with a cloud-based automated farming platform, allows us to provide AI-based solutions to farmers despite poor network and registration infrastructure. They present a contextual study demonstrating how our infrastructure, when coupled with a soil dampness sensor, can be used to more efficiently manage water resources.

To address the wide variety of problems observed in agriculture, a customer-centric IoT architecture was provided [39]. The suggested framework would let ranchers systematically inspect their remote fields, earning them praise for producing high-quality harvests. The planned layout also improves the food chain in a way that allows farmers and ranchers to increase their overall profit from the items they sell. The viability of the proposed engineering is evaluated using various usage scenarios that include various stages of the agricultural cycle. Reports also suggests a revolutionary structure for high-end mobile phones, which would inspire product designers to develop apps necessary for implementing the framework's many features.

P. Assuredly et al. [40] investigated a prototype in which two different sensors, a frequency domain reflection sensor and Resistor-based (RB) sensor, were used in this minimal effort WFD planning observational study to find moisten fronts. The study finds an inference to IOT-WFD as an innovation that provides constant wetting front data in soil, with precision agriculture and an efficient water system area, as well as connected choice information that conforms to the prevailing technological trend and the needs of smart farmers. This prototyping overview has been shown to have beneficial impacts, and evidence has been provided.

Ferrag et al. [51] examine how green agriculture will make use of blockchain-based solutions that prioritise privacy and consensus methods for IoT applications. Additionally, blockchain-based privacy solutions and consensus algorithms for IoT applications were investigated, along with their potential adaptations to environmentally friendly agriculture based on the Internet of Things. Future research paths are discussed in the area of green agriculture are discussed, and open research issues are underlined based on the current survey.

Devices, platforms, network protocols, data processing technologies, and possible agricultural applications of smart farming with IoT have been extensively studied [54]. The analysis demonstrates how data processing has progressed over time. Data was often used reactively in conventional methods. However, advances in technology have enabled new methods of using data for crop problem prevention and improved diagnostic precision.

To provide data-driven insight and decision-making to encourage the development of aquaculture in a way that is environmentally sustainable, [55] brings together partners from industry, technology, and academia. The first case study of IoT instrumentation, information, and effect on the aquaculture sector was provided. The difficulties of connection, interoperability, and standardisation are examined and show how our past actions might guide our future plans.

Jacopo Aleotti et al. [57] suggest components of the automatic precision irrigation system that are managed. The embedded IoT devices operate linear irrigation equipment as part of the distributed design, which also consists of a decision support system, a server node, a mobile application for user engagement, and other aspects. The farmer can use the mobile app to register his information in the decision support system, ask the server for an irrigation plan, and monitor things in real time. The primary components of the system were tested in tomato fields in preliminary studies.

The conceptual model described in [60], which was developed as part of the SWAMP project. After surveying all relevant literature, they present a conceptual model for predicting and explaining the investigated behaviour, one that draws on IoT, TPB, and Agriculture 4.0. Multiple actions that may be taken by the various players in the agricultural environment can be analysed using this model. With an emphasis on operations planning and irrigation scheduling, this model can be used to construct relationships between the measurements associated with each defined variable in a data model. The models shown here show how IoT and Industry 4.0 technologies can considerably improve strategic planning, operational optimisation, and intelligent water preservation in the agricultural industry.

A. K. Pandey et al. [61] presented an automated IoT-based smart polyhouse system using Hadoop technology. The suggested nonmanual approach aids in automating the functionality of polyhouses, which in turn increases crop output and quality. Sensors, IoT gadgets, and Hadoop technologies like Apache Hadoop, Flume, and Hive make up this system. Sensor data will be analysed with these tools to better inform policy making. It also emphasises the use of smart irrigation methods and technology within the greenhouse, such as drip irrigation, to help farmers protect their crops from flooding.

Researcher S. Rajeswari et al. [62] collected agricultural data using an IoT device, which was then uploaded to a cloud-based database. Big data analysis performed in the cloud is utilised to examine visual information. Needs for fertiliser, crop analysis, market research, and crop stock. The farmer receives the results of the forecast, based on data mining technology, via a mobile app. The ultimate goal is to use these forecasted data to increase crop yields while keeping agricultural costs low.

A disease-detecting intelligent automatic watering system is described [68]. Moisture sensors, temperature sensors, and wetness sensors are all part of the system design and they will all be placed in agricultural fields where collected data will be compared with threshold values calculated for different types of soil and different crops. An Arduino Uno processor receives data from the deployed sensors and communicates wirelessly with a data centre via a GSM module. The data centre stores the information it receives so that data mining techniques such as the Markov model may be used to analyse the data and identify potential diseases. When all is said and done, Android smart phones are updated with analytical results and observable physical metrics. The Arduino is programmed to turn on and off the irrigation system pump via the smartphone's user interface when instructed to do so by the user's Android device.

A new privacy-protecting multi-agent system (MAS) created [72] for an IIoT environment. To choose and build the right clusters for the IIoT system, an expanded moth swarm algorithm-based clustering (EMSA-C) method was first created. Additionally, a multi-agent system is implemented to provide encrypted exchanges between different clusters. The potential is investigated through a comprehensive comparative study, with outcomes evaluated across a range of metrics. The investment money needed is substantial. The high cost of implementation is an evident issue for industrial IoT. The huge volume of data generated by IoT devices makes secure data storage and management connection failures common. The simulation findings show that BDL-PPDT is superior to current approaches in terms of output. The provided BDL-PPDT method may only have a 98.15 percent success rate, but it yields the finest attainable result nonetheless. The BDL-PPDT approach was demonstrated to be superior to the other existing methods by a number of criteria and is advised based on the findings of the aforementioned data analysis.

Using the IoT to perform a variety of outdoor tasks, a revolutionary wireless mobile robot was created and launched [81]. Agriculture, transportation, and water distribution can all benefit from the findings of this study. The IoT and remote sensor system is used to create sophisticated agricultural frameworks in many regions of the world. In this regard, one of the offshoots of intelligence is the practise of exactness. Researchers have developed a wide variety of check and robotization frameworks for a variety of agricultural applications. Using WSN, data gathering and transfer between ranch-based IoT devices will be a breeze.

An IoT-integrated system was designed for crop production [82], which makes use of cloud computing for crop monitoring and other purposes. The technology is useful for monitoring crop growth in real time and saving the farmer time and effort by analysing data from sensors already embedded in the crops.

The IoT ecosystem, as described by Olakunle Elijah et al. [88], enables smart farming. In addition, we present upcoming trends and possibilities that are broken down into four distinct sections: technology developments, application scenarios, business, and marketability.

Rashi Kaur et al. [89] provides a comprehensive method for tracking and adjusting key aspects of crop development and harvesting. Technology also uses machine intelligence and the IoT to predict crop production.

Using inexpensive IoT sensors and widely used IoT-based information storage Luis Omar et al. [95] presented a farming system. In addition, a novel data-mining method is offered for the forecasting of the output volume from various data sources, which uses crop production and weather data. To begin to validate this strategy, open historical data were collected from authorised sources in the north-eastern part of the Mexican state of Puebla.

The main goal of the case study is to develop a model that predicts high-yield crops and precision agriculture [98]. The suggested system modelling incorporates cutting-edge IoT and important agricultural strategies. The final goal of this case study is to develop a model that can predict high-yield crops and precise farming. The suggested system model incorporates both critical agricultural measures and contemporary technology like the Internet of Things (IoT).

N Singh et al. [103] highlight in their proposal the importance of creating a helmet equipped with IoT. The location of the miner can be monitored with the help of an integrated GPS tracker. The proposed work would reduce the likelihood of fatalities and accidents in high-risk settings. This work is assessed in three distinct settings using an accuracy metric. The results of the study indicate that the suggested prototype achieves an accuracy of around 96% in the indoor setting, 98% in the outdoor setting, and 97% in the industrial setting.

2.1.2 Smart Farming Based on AI/ML/DL Techniques

To automate urban farming evaluation, an IoT platform is described [10] that brings together IoT, big data and distributed computing. Customers, in particular ranchers, will be able to keep an eye on the weather and automatically adjust the supplement thanks to the IoT platform. Based on the information collected about temperature, pH, total dissolved solids (TDS), oxidation reduction potential (ORP), and TDS, the platform suggests supplements. Regular camera checks are used to observe the plant's development rate. The proposed architecture uses a WiFi-based network and the Message Queuing Telemetry Transport (MQTT) protocol to transmit sensor data from an Internet of Things (IoT) device to a cloud-hosted worker. The platform is web and mobile based, giving customers the freedom to check in on the urban ranch anytime they choose.

A novel idea for the preservation of rural land is proposed [11]. The PiCam is triggered to take a picture of the area in response to suspicious activity and motion around the ranch. To identify what is shown in the image, the image processing component uses single shot IDs and Mobilenets, a Deep Learning technique implemented in OpenCv for the Raspberry Pi board. The rancher will receive this notification in the form of email and wire equipment. The experiments are carried out on a ranch, and the precision and regularity of the framework are calculated and planned. Based on the data, it is clear that the framework is both highly accurate (92%) and predictable (100%) in identifying malignant progression.

IoT, big data, and AI and their complicated roles in influencing the future of agri-food systems were depicted in a diagram by Misra et al. [13]. The authors cover the role of IoT and big data investigation in agriculture (including nursery check, clever homestead machines, and robot-based harvest imaging), supply chain modernisation, online media (for open advancement and feeling examination) in the food industry, food quality assessment (using ghostly techniques and sensor combination), and finally sanitati after a brief introduction to the IoT, massive data (big data), and AI. The commercial viability of applications and the findings of translational research are particularly of particular attention.

The data and the warning message were handled using an AI calculation to produce a warning message, and eventually the data and the warning message were shown via a graphical user interface (GUI). Araby et al. [18] communicated a detecting organisation to collect field information of specific harvests (potatoes, tomatoes, etc.). To predict late scourge sickness in potatoes and tomatoes before the major event, this research suggests a clever system based on the coordination between IoT and AI, reducing costs by alerting the rancher to the precise time to apply protective pesticides, which will help preserve yield production during contamination seasons and reduce the use of unnecessary pesticides.

The purpose of this framework [19] is to develop continuous weed control for onion farms. This system will be able to recognise weeds and apply the right dose of herbicide. The proposed WCS is a practical, portable, and easily operated remote arrangement of portable supplies accessible via a straightforward web interface. It is programmed to automate weed management, making it easier for ranchers to keep their fields in order. Image processing, artificial intelligence, and IoT are all crucial to the suggested architecture.

The RiceTalk project [23] uses nonphotographic IoT devices to detect the effects of rice. Our agricultural sensors produce nonpicture information that may be gradually processed and broken down by the AI instrument, in contrast to the picture-based plant infection finding approaches. RiceTalk's AI model stands out because it is managed in the same way as any other IoTdevice. Our approach significantly reduces the overhead incurred by the board in order to provide continuous planning and forecasting. They also offer a novel component for spore germination as an alternative farming approach for extracting elements. In its present form, RiceTalk's prediction of rice's effect is 89.4 percent accurate.

The data collection system demonstrated [30] is based on IoT technologies and intelligent image recognition. Decisions on what to grow involve a lot of knowledge, but the suggested framework would make it possible to automate the harvesting process by recognising individual crops using neural network models. After performing article placement on images, the usage of pixel orientations of the primary concern of the objective harvest in the image as neural organisation input, with the robotic arms being read as the yield side. A single shot multibox recognition model in the back layer and a photo highlight extraction model created with a MobileNet variation 2 convolutional neural network were combined to create the article locating model. At that time, the model was able to identify crops by collecting and labelling images. The results showed a mAP of 89%, while the mean Average Precision (mAP) of the suggested model preparation was 84%, which was higher than that of other models.

N. Ippo et al. [33] have provided rural IoT framework solutions for the development observation of the tomato natural product by growing the Slack Bot API. This will inform ranchers about the condition of the tomatoes. By using deep learning to recognise organic tomato products, picture training to extract colour highlights, and artificial intelligence to score the different growth phases, they also pioneered image analysis. Their tomato discovery approach allowed users to choose between identifying green and red vegetables based on the first images provided. In addition, they have achieved a weight accuracy of 91.5% while employing SVM Classification to characterise the six stages of tomato growth. They may use the results as a guide and estimate for when to harvest the tomatoes. Their study will conclude with the use of images from predetermined locations for the purpose of classifying and identifying diseases that manifest themselves on the leaves and fruit of tomatoes.

The Adaptive Plant Propagation Algorithm, a novel soft computing strategy, was presented [42] to determine the ideal locations for these mobile nodes. The deployment of these movable target nodes occurs in an anisotropic setting characterised by irregularity. Compared to existing meta-heuristic optimisation methods, the suggested APPA algorithm shows superior performance in simulation results for localisation error, computing time, and detected sensor nodes.

An energy autonomous system that can run continuously without human intervention across low power wide area networks [58]. They used a solar panel that was a few hundred square centimetres in size to create an application for a low-energy platform. The low-power foundation for an ML algorithm provided by the solution enables speedy IoT prototyping. In-depth analysis of the network model has revealed the parameters' settings and the limits of the requisite hardware. The effectiveness of the suggested system is evaluated and some thoughts on how to reduce power usage until the system has a net negative energy output.

An energy efficient routing technique that integrates localisation and clustering was proposed [59]. To pinpoint the location of each node, an RSSI-based localisation approach suggested. Next, an uneven clustering technique based on fuzzy logic is created to ensure that all sensor nodes use the same amount of energy. PanStamp NRG 2.0, a wireless sensor node, is used to really build an energy-aware routing algorithm. This network architecture is easily adaptable to IoT systems for use in environmental and agricultural monitoring and control.

Using IoT, ML and drone technologies, an integrated strategy for tracking crop health developed [63]. When these diverse types of sensing are combined, the resulting data are inherently disparate because of differences in nature (i.e., the observed parameter) and in temporal fidelity. The suggested method aims to maximise the integration of multiple sensing modalities and make their practical implementation easier due to the fact that different techniques have different degrees of spatial resolution. In their suggested system, IoT sensors report on the present condition of environmental parameters impacting the crop, and multispectral data from a drone platform. Because it measures crop health based on chlorophyll content alone, the NDVI can only tell us so much. Data from IoT sensors and multispectral images, both of which comprise time series data with various durations, have to be translated into a fixed-sized representation to create crop health maps. The neural network with multiple layers provided the highest precision (98.4%) of all evaluated models after the data were processed using a variety of ML and DL techniques. Due to a lack of baseline information, the accuracy of the health maps was double-checked by conducting ground inspections and consulting with agriculture specialists. The suggested study is a locally developed, technology-based approach to agriculture that can reduce the need for crop ground surveys while still delivering significant information about the health of the crop through the extraction of complementing features from a multi-modal data set. This is especially useful when there is a lot of agricultural land.

A new federated framework, suggested by TKAGFL [69], which made up of these three elements: update approach, data heterogeneity, and scalability. As a first step in addressing the problem of data heterogeneity that usually arises in actual federated learning, conditional generative adversarial networks (GANs) are suggested as a method of data preparation. Second, the enhanced homomorphic encryption approach alleviates the tensions that arise from exchanging data and protecting individual privacy. Third, the authors increase communication efficiency by compressing communication parameters using a combination of top-K methods and the traditional AdaGrad optimisation used in deep learning. According to the test results, our TKAGFL framework can converge at 150 communication rounds, which is 50 rounds sooner than the competition, and it is 15% to 20% more accurate than rival algorithms and frameworks. It is also helpful for federated learning applications in industry, since our TKAGFL method decreases communication traffic by a factor of 10.

To optimise the classification and feature extraction processes, [70] looked at principal component analysis (PCA) was used to reduce dimensionality in a deep learning model created using the Debrecen Diabetic Retinopathy Debrecen Data Set, which is available in the UCI ML repository.

To predict agricultural productivity and drought, Nermeen Gamal Rezk et al. [74] suggest an intelligent farming system together with an efficient prediction method called WPART based on ML approaches. The suggested approach is estimated using five different data sets. The results demonstrated that the proposed method performed better than existing methods in classifying and forecasting agricultural productivity and drought. The results revealed that the suggested strategy was the most effective in forecasting drought and measuring the yield of crops including Bajra, Soybean, Jowar, and Sugarcane. The WPART approach outperforms state-of-the-art gold standard algorithms with accuracy levels of 92.51%, 96.77%, 98.04%, 96.12% and 98.15%, respectively, across five datasets assessing drought categorisation and crop yield.

Using a sensor network, the data collected [75] from a number of different crop fields (potatoes, tomatoes, and more), sent them to a ML algorithm to generate alarm message, and displayed via the GUI.

Various ML strategies developed [76] to predict CLW infection in plants. This study laid the groundwork for using ML to foresee the presence of CLW in greenhouse crops. In a commercial hydroponic greenhouse, the moth of CLW data was gathered weekly for two years. Temperature and relative humidity readings were also taken continuously during the investigation. The XGBoost algorithm was found to be the most efficient algorithm used throughout this research. This algorithm has attained an accuracy in prediction of 84%. To guarantee a complete data set for future outcomes, authors investigated the effect of several environmental factors on prediction precision.

Remote monitoring of rice paddies using deep learning and IoT is proposed by Prabira Kumar Sethy et al. [78]. For rice leaf disease detection and nitrogen status assessment, the pre-trained vgg16 network is being investigated. In this context, transfer learning and deep feature extraction are used to recognise photos. SVM have been introduced to identify pictures with the deep feature extraction method. Vgg16's transfer learning method achieves 79.86% and 84.88% accuracy, respectively, when used to recognise four distinct leaf diseases and forecast nitrogen status. The deep features and the SVM findings both have a 97.31% and a 99.02% accuracy rate in recognising four different leaf diseases and predicting nitrogen status, respectively. Additionally, an IoT-based and deep learning-based architecture is proposed for remote field monitoring. The proposed prototype has advantages over the state-of-the-art in that it not only regulates temperature and humidity, but also monitors the additional two factors, including the detection of nitrogen status and illnesses.

The proposed Smart Agriculture approach [79] includes monitoring the agricultural land and can greatly help farmers in increasing output. The cloud-stored data, which contain details like the temperature, moisture, and humidity that affect disease in an agricultural field, is subjected to a naive Bayes analysis.

An IoT-enabled agricultural monitoring prototype was proposed [80], which would use a variety of algorithms to monitor crops for a variety of things, including detection, quantification, maturity testing, and disease. This article discusses intelligent farm monitoring solutions enabled by IoT. Agricultural veggies have been detected and quantified using CHT. Defects in vegetables have also been identified by the use of colour threshold and colour segmentation. All methods were designed and implemented using convolutional neural networks (CNNs), a ML technique. To determine which approach would be best for integration into this agricultural monitoring system, MATLAB simulations have been used to compare traditional methods with CNN. This study found that CNN outperformed other approaches and existing algorithms with an accuracy of 90% or higher, making it the preferred option.

The importance of various emerging automation techniques highlighted [83] such as IoT, WC, ML, AI, and deep learning as part of the technological growth of the sector.

Guanghui Ren et al. [84] described contemporary sensing applications that take advantage of ML-enabled smart sensor systems. Using both traditional and cutting-edge ML (ML) algorithms and state-of-the-art computer hardware, smart sensor systems have developed highly specialised, application-specific "smart" models that can fuse multiple sensing modalities into a single, comprehensive picture of the system under study.

Using data analytics and machine learning in an IoT system, Ravesa Akhter et al. [86] created a prediction model for Apple disease in apple orchards in Kashmir valley. To find out how farmers felt about the impact of evolving technology on precision agriculture, a local poll was also carried out. The study also explores the challenges of incorporating new technology into tried-and-true farming practices.

Vu Khanh Quy et al. [87] evaluate the architecture, applications and research plans in addition to IoT devices, communication technologies, and big data storage and processing. The results of this research will serve as solutions that improve agricultural output and quality.

To meet the long-term demands of smart agriculture, Yinghan Liu et al. [90] have developed an IoT and ML-based platform for smart agriculture and designed tests to test its efficacy. In addition, this study combines the demands of long-term smart agricultural development to create a platform for such development that makes use of IoT and ML and then uses experimental design to prove the platform's efficacy.

To increase cattle productivity, Arpit Jain et al. [91] employed ML models and collar sensor data to make predictions about reproductive patterns, feeding difficulties, and bovine behaviour. The main areas of interest include the prediction of soil properties such as organic carbon and moisture content, the prediction of crop yield, the detection of disease and weeds in crops, and the identification of species. It is vital to categorise various crop pictures in order to monitor the production and quality of crops. Examples of how this approach may be used to increase livestock productivity include using ML models to predict reproductive patterns, diagnose feeding issues, and analyse cow behaviour using information acquired from collar sensors. Drip irrigation and other intelligent harvesting systems, both of which significantly reduce the need for human effort, are also discussed.

N. Sandeep et al. [92] looked at several different ML methods, each with its unique process and benefits and drawbacks. The best results from using any given model will result from the user having a thorough understanding of that model before using it in practise. Smart farm management can boost agricultural output by making better use of available data through analysis and processing. New possibilities for data-intensive science have arisen thanks to ML and high-performance computers.

Shekhar Bhansali et al. [93] investigate the applications of several ML Designs to the analysis of sensor data in a farming context. The article continues with a case study of a data-driven Internet of Things-based smart farm prototype that serves as an integrated FEW system.

Using the IoT and ML/Deep Learning technologies, Alberto Ruiz et al. [94] offer a novel architecture for continuous monitoring of crop quality in agriculture. This three-tiered design is used to compile information from many sources and analyse it for conclusions on crop quality. The proposed method, which is based on the combination of data from various sources, achieves a smaller percentage error than using only one source, according to experiments. For example, compared to a strategy that relied solely on sensor data, our method obtained a 6.59 percent error rate in the test data set.

By outlining the benefits and pitfalls of deep learning in agriculture, Biyun Yang et al. [96] serve as a valuable resource for scholars. This paper was written to help academics better grasp the potential benefits and drawbacks of using deep learning in the agricultural and horticultural industries. The author also hopes that this study would spur the development of intelligent horticulture by inspiring academics to investigate some important applications of deep learning in this field.

Artificial intelligence (AI) may be used to estimate plant health in place of human understanding of sensor data, as proposed by Davor Cafuta et al. [97]. Extra time between harvests and a higher nutrient yield are both possible thanks to inferences about a plant's status. For the purpose of estimating plant health, an approach is provided in which artificial intelligence is used in place of human expertise gleaned from sensor data. An accurate assessment of plant health lengthens lag times and increases yield per unit of input nutrients. The cost of plant research may be lowered and its usability and reliability boosted by the use of intelligent design and artificial intelligence algorithms to the study of plants. As a result, our improved greenhouse would be useful for studying and cultivating plants.

Dimensionality reduction methods were the subject of research [100]. The results of the experiments show that ML algorithms using PCA improve performance in high-dimensional datasets. ML methods without dimensionality reduction have been shown to perform better when the dimensionality of the data sets is minimal.

Using deep learning (DL) methods, K. Lakshmanna et al. [101] took advantage of the plethora of new data that were collected or generated. Both DL and IoT approaches have grabbed the attention of many academics due to the growing popularity of the many application domains. Research has pointed to DL as a workable option for managing IoT generated data because of its design for dealing with several types of data in large volumes, which requires near-real-time processing. The author elaborates on several DL methods by detailing how they operate. The author conducted a comprehensive review, summarising the most significant DL reporting initiatives across datasets. Motivation and inspiration may be drawn from discussions about the capabilities, applications, and problems that DL leverages to enhance IoT applications.

A methodology to aid diabetics in rural areas is developed by D S Rajput et al. [104]. It is useful for identifying Type 2 diabetes sufferers in rural India. It enhances the conversation between patients and medical professionals. The objective of this study is to generate a list of probable threats and their connections. In this study, several different ML models are used for prediction in this study, and their performance is evaluated so that the best one can be selected. These models include LR, SVM, decision tree, Naive Bayes, and K closest neighbour classifiers. Compared to other methods, SVM has the highest accuracy, at 96.0%.

2.1.3 Smart Farming Based on Fuzzy Logic Approach

For the purpose of autonomous nursery, FLCs have IoT capabilities has been developed [9]. Seepage pH and Electrical Conductivity (EC) estimates are also evaluated together with the computer-generated waste estimates. The lexical vulnerability provided by "effectively inaccessible" was evaluated to ascertain whether water content is actually accessible to crops, just as yield is given a scalar value related to fertigation. The final product is a regulator that incorporates fundamental human information about water system planning into a systematic FLC, giving rural researchers quick access to the fundamental factors related to creation and development for a given space. Valid data collected from two distinct harvests using Internet-connected remote sensors was used to gain regulatory approval. The findings of this study support to the continuous creation of low-cost, yet useful applications based on FLC and IoT that provide agribusiness manufacturers in poor nations.

K. Omar et al. [41] improved the system's overall performance, analysed the SE and EE issues plaguing 5G networks using a fuzzy-based technique using a lookup table, and discovered a good balance between the two. A maximum EE and a 5G network with cognitive radio support had EE and SE values of 0.92 bits/J/Hz after changing the secondary user's (SU) sensing time and transmission power.

2.1.4 Improved Agriculture Based on Wireless Sensing / Communication Technology

Advancement of horticultural equipment and software libraries is two areas where the author has contributed [4]. A discussion of early-stage companies, public and private sector initiatives, and creative and practical solutions for precision agriculture is also included.

Rural and animal situations [7] are not effectively digitised because they operate with less resources and a lower baseline of technology than the commercial sector. For the agri-food industry to adopt, SF, PA, and Industry 4.0 provide promising new ideal models.

Wireless sensor networks (WSNs) have been looked at in high-tech farming [8]. The physical and functional force utilisation of the various WSN components is the main focus of this article. From an energy efficiency point of view, this study surveys and discusses the most widely used conventions at the physical, information connection and organisational levels. The study findings provide concrete, verifiable evidence of primary power consumers, the scope of their consumption, and a thorough understanding of the critical elements that must be implemented to boost energy efficiency in a WSN. The investigation also recalls a WSN action performed for a sophisticated horticulture application.

S. Akatamreddy et al. [12] look at the practises and technologies employed in precision farming that are shared with Industry 4.0. This article also discusses the gaps that need to be filled by examining innovations and recommendations and recommending a combined engineering approach. It is hoped that filling these gaps would hasten the development of Agriculture 5.0, which will involve fully automated measurement control.

Archbold Taylor et al. presented an IoT framework for pH determination [20] for use in precision agriculture. The prototype is developed in IoT engineering, including data collection, processing, centralization, and user access. Each module's exploratory approval measure is taken into consideration throughout the planning phase, as well. They showed that the system could make predictions at a variety of points in large areas for the adjustment model.

M. Baghrous et al. [21] have presented a system for autonomous farming that is based on the fog processing viewpoint with LoRa technology. The results demonstrated that continuous handling, response time, and data transmission capacity will be improved in agriculture by implementing a fog computing paradigm. They present an alternative arrangement based on Fog Nodes (FN) and LoRa technology in order to reduce the absolute dormancy induced during information transmission from these inertness sensitive robots/robots towards the Cloud for preparation and improvement of hubs organisation in the vast brilliant homesteads.

For mobile IoT networks, a link quality-orientated routing (LQOR) standard proposed [25]. By carefully selecting the next hop with fewer neighbouring hubs, this strategy aims to balance the load across the organisation. The computation has been shown to have a positive effect on the evaluation of similar presentations compared to other comparable approaches in the literature. The results demonstrate that the suggested computation reduces the number of retransmissions of information and the number of bundles affected by misfortune. As a result, the performance of the framework is enhanced in all aspects and the lifespan of the organisation is increased.

Karim et al. developed and piloted [26] a cloud-based emotional support network against a late-breaking disease. To stop the potato disease, they implemented an alternative social support system. This is done by helping ranchers in implementing effective disease treatment strategies using weather data and the "Ullrich" forecast model. A cloud worker was also deployed to store the information gathered from the distant sensor network on the humidity and temperature conditions in the crops. The "Ullrich" model's risk factor counts were used to create an early warning system that sent an SMS to the rancher at the first sign of the “late blight” disease. By comparing their suggested framework with state-of-the-art DSS, they found it to be more widely available at a lower cost.

To increase nurseries’ productivity and accuracy, we report the development of a portable LoRaWAN passage device [28]. The recently unveiled technology makes use of a Heltec Raspberry Pi 3 B + restricted Mini LoRa Gateway. It uses a predetermined number of sensor-equipped LoRa hubs and is powered by an external Li-On battery. The sensor data on humidity and temperature will be compiled by the adaptable LoRaWAN gateway. These records are compiled using publicly available, no-cost web-based services. This study describes and clarifies the favourable circumstances and use of information gathering in agriculture.

Home ranchers are urged [29] to monitor the moisture and temperature using a low power and adaptable IoT-based engineering to evaluate the ecological influence on plants. The passage application running on a mobile phone transmits the door's purposeful properties through Bluetooth Low Energy (BLE) to a cloud platform that stores and cycles the data. These data are helpful for home ranchers because they have time-sensitive information, such as when to water a plant or when it is at risk of contracting a disease. This information is crucial as it helps reduce yield disappointments and makes farming more efficient. The new apparatus and software engineering are adaptable and designed to use less energy. Research into monitoring the microclimate will be aided by analyses that show that it is possible to construct a high-spatial target by locating multiple sensor hubs in a small region.

A user-friendly and customisable engineering [31] for implementing recent advances enabled by IoT in SF is shown. Unmanned aerial vehicles (UAVs), wireless sensor networks (WSNs), weather stations, and a data processing architecture that takes advantage of AI and registration breakthroughs are all used in the suggested approach. The proposed architecture develops from the creation of a network of watchers and decision makers who cooperate to safeguard plant capital from risks from the outside (environment and pests) and inside (diseases).

Singh, M., et al. [43], used a search table with energy harvesting (EH) to solve a problem. Provides the highest possible throughput with the lowest possible energy consumption, making it possible to build self-sustaining all-encompassing wireless networks. The simulation is performed with NS-2, and, for readability, the results are displayed in Matlab. The findings demonstrate that the suggested model uses less energy and provides a better normalised attainable throughput than the current approach.

Hassan et al. [44] focus on the methods and procedures that improve spectrum efficiency and performance, attempting to examine and survey them. The important functionalities of the spectrum optimisation methods were evaluated using a descriptive method. These are efficient ways to address issues associated with a certain frequency range, and they would also give benefits in terms of spectral efficiency.

An analysis proposed [45] a system and analysed existing and past research work that talk about the main components, benefits, and limitations of the greenhouse system. The fundamental goal of this effort is to demonstrate and catalogue greenhouse features taken into account in each research gap. Agriculture growth in entirely controlled systems can currently not able to be monitored in greenhouses due to a lack of suitable alternatives. This study recommends a smart greenhouse system for use in the sector of precision agriculture for remote monitoring and control.

A review of previous research was conducted [46]. Collaborative information analysis, intelligent assisted diagnosis, healthcare information technology, and patient monitoring are the four most recent advances in this field.

Using MATLAB simulation software, M. Hassan et al. [47] study simulation results that demonstrate that increasing power improves the capacity rate and user count better than increasing BW, and the results also demonstrate that as the number of SC-NOMA users increases above a certain point, the capacity rate of the overall network drops.

Many features of spectrum sharing and management were summarised in [48]. The goal of this comparison is to help engineers create a 5G and beyond network that makes the most effective use of the available spectrum.

Proactive spectrum sharing with full-duplex (FD) in cooperative Cognitive Radio Networks (CRN) was proposed. It is Analysed and discussed in detail for smooth system conduction [49].

The solutions presented [50] are based on the Floating Admittance modelling of basic L-, T-, and -type filters. When considering the size and complexity of circuits, the floating admittance matrix approach is a clear winner.

An approach to data analysis and processing for decentralised crop and soil monitoring was presented in [64], with the help of hierarchical aggregation and modelling primitives, which strengthen the network by removing communication bottlenecks. The main aim is to utilise computing resources at individual nodes using the fog computing paradigm and convey the events that arise to infrastructures for higher-level decision-making. Improvements are highlighted by reporting key metrics. Constraints on operations and rollout are anticipated after a case study is conducted using actual field data for crop and soil monitoring.

Data gathered [65] from a real-world wireless deployment in a natural forest setting (the ECOMESH test bed). Additionally, two empirical models were created that can be used to forecast the performance of an attenuation network under two distinct conditions. These models provide the foundation for a dynamic network management system that may be used to keep QoS guarantees in place across a wide variety of wireless network topologies.

A prototype was developed [66] for the detection and measurement of pig growth. An improved watershed algorithm is applied to the depth images collected from the time-of-flight camera in the selected region of interest to segment each individual animal when there is significant occlusion. The growth rate is projected using the segmented linear fitting approach, with the weight of the pig determined using image-based data. Farmers may get immediate, actionable insights about what is occurring in the pig hen based on the collected data. The promising potential of precision agriculture techniques in livestock production to increase production and improve animal welfare has been shown by preliminary findings.

A new M2M Communication Stack is suggested [67] to the specifications of the Sheep IT project, but with broader applicability in reference to intelligent farming. This study presents both a definition of the stack and experimental findings that validate the stack's viability.

To maximise energy utilisation and network longevity, an improved IMD-EACBR technique presented [71] for WSN. The IAOAC algorithm determines a suitable goal that links various structures based on criteria such as energy savings, detachment, node degree, and intercluster distance. Several facets of the performance of the IMD-EACBR model have been investigated. The last step is extensive testing of the proposed network utilising all of NS-3.26's simulation features. Improvements in packet delivery ratio (PDR), latency, energy consumption, and number of dead nodes are among the other metrics that stand out from the simulation findings.

Challenges and complications that may be encountered when integrating modern farming practices with older methods of production. The use of statistical and quantitative techniques can lead to revolutionary changes in our current agricultural system. The current and upcoming agricultural trends are provided through systematic analysis.

In their comprehensive review of smart farming techniques and designs, they provided [77] an in-depth analysis of various designs and viable recommendations to fix the current state of smart farming.

For long-term prediction of several environmental parameters in the presence of substantial non-linearity and noise, architectural application in a smart greenhouse is provided [85]. The suggested BEDA technique provided the best model across all datasets, with R values with root mean square errors of prediction for the three parameters of 2.726, 3.621, and 49.817. The experimental findings demonstrate that the suggested technique is ideal for more exact greenhouse management due to its high degree of prediction accuracy, resilience, and generalisability.

An improved method for choosing CHs is presented [99], which makes use of a variant of the Rider Optimisation Algorithm (ROA). Using the best fitness value, the suggested method divides the solutions into two groups. The first set is kept up-to-date with the averaged value of riders who are being bypassed and riders who are being followed; the second set is kept up-to-date with the averaged value of riders who are being attacked and riders who are being overtaken; the latter is known as Fitness Averaged-ROA (FA-ROA). Through a comparison with other state-of-the-art optimisation models, the proposed FA-ROA's performance is validated with respect to both the percentage of active nodes and the normalised energy.

To reduce the density of superfluous routing (DSR), K. Lakshmanna et al. [102] use the perimeter degree method (PDT) to quantify routing congestion in both the horizontal and vertical directions for a silicon chip area. The last two decades have seen a rise in popularity for a metaheuristic approach to computing. It is a popular issue in optimisation and a classic problem in graph theory. Despite its widespread use, it is flawed because it gives incorrect guidance on where and how to place nodes. In order to evaluate the amount of congestion that occurs during the routing process and decrease the amount of congestion that occurs, the optimised model created by the improved harmonic search optimisation algorithm is tested and analysed with the improved floorplan data.

W. Wong et al. [52] conducts a detailed examination of the current greenhouse cluster control system, analysing its features from the point of a hierarchical control system. Finally, the important features of hierarchical control in greenhouse clusters are shown from the perspective of application research. For creating models of greenhouse cluster coordination description and control structure, complex system theory offers significant theoretical help.

A comprehensive look at privacy and safety in a smart agricultural environment was offered [53]. The security and privacy concerns of a cyberphysical system explored that is both dynamic and widely dispersed, with a focus on the precision agricultural area. In addition, the author provides greater detail on possible cyber-attack scenarios and draws attention to current research problems and future prospects.S. M. Patil et al. [56] used Kalman filter (KF) with prediction analysis to gather noise-free data for transmission in cluster-based WSNs. This method reduces the burden of data transfer in WSN applications while simultaneously enhancing the quality of the data used for analysis. Prediction analytics, such as a decision tree, are used to forecast things like agricultural production, soil type, precipitation, and even crop diseases.

2.2 RESEARCH ANALYSIS AND RESEARCH GAP IDENTIFICATION

The findings of the previous study, which are summarised in Table 2.1, demonstrate that environmental conditions can be analysed using agriculture growing monitoring techniques.

Table 2.1 Research analysis and research gap findings in existing literature

Ref	**Sensors/Actuators Used**	**Technology Used**	**Application**	**Research Gaps**
[1]	Temperature/Humidity, Electrical conductivity, pH, Level controller, Liquid counter, Flow meter, Solar radiation	IoT,	Greenhouse (prototype)	The cloud cannot provide very low latency.
[3]	Temperature	IoT, Petri Net	Greenhouse	Focused on energy consumptions parameters only, no provision of intelligence system
[7]	-	IoT, DL	General Farming	High computational cost not suited for IoT
[8]	-	Energy Efficiency	General Farming	Limited range of implement devices also no provision of AI
[9]	pH, EC, ambient temperature and humidity	IoT, Fuzzy Logic	Greenhouse	Human knowledge and expertise are fully dependent on Fuzzy Logic control systems.

[11]	PIR sensor, Camera	Image Processing, OpenCV	Agriculture Field	To shorten the time taken for a notification to the extent of a user, picture compression techniques must be created.
[12]	-	IoT, ML	Agriculture Field	The crop data set should be precise according to environmental conditions
[14]	Air/ Soil Temperature and Humidity	IoT	Vegetable Garden	The energy consumption parameter didn't consider
[17]	Temperature, Pressure, Humidity, Luminosity, Soil Moisture, Relay Switch	IoT	General Farming	Practicality implementation will be issue
[18]	Air temperature sensor, air humidity sensor, and soil	IoT, ML	General Farming	High bandwidth, high power consumption, less reliable
[19]	Camera	IoT, Image Processing	Crop Field	Maintenance of the robotic structure yields higher cost
[21]	water level, EC-pH level,	IoT	Agriculture Field	It is not scalable as cloud
[22]	temperature and relative humidity sensors, pump	IoT	Vertical Farming	Very few parameters studied
[23]	Temperature, Pressure, UV, CO2, Rain Gauge, Humidity	IoT, AI	Rice Field	Security is not considered

[24]	Temperature, Pressure, UV, CO2, Rain Gauge, Humidity	IoT, AI	Turmeric Field	Latency and Security is not considered
[26]	Temperature and Humidity	IoT,	Potato Field	The bandwidth is increased with higher power consumption
[27]	Camera, Temp and Humidity, PIR,	IoT	green vegetation, poultry, Fish Tank	Implementation is not considered
[28]	Temp and Humd	IoT, LoRa	General Farming	Lack of an effective storage mechanism
[29]	Soil Moisture , Temperature and Humidity	IoT, BLE	General Farming	Rusting of soil moisture sensor
[30]	Camera, robotic arm	IoT, Image Processing, MLP	Tomato Field (prototype)	Maintenance and precision of the mechanical part increases the cost
[31]	Camera	Image Processing, ML	General Farming	Power consumption and security need to improve
[33]	Camera,	IoT, DL, ML	Greenhouse	High computational cost
[35]	Humidity, Temperature, Moisture, Intensity	IoT, Threshold Control	General Farming	Presentation is not user friendly
[36]	Temperature, pH	IoT	Chilli Farming, Irrigation	Power consumption need to analyse
[37]	soil moisture, air	IoT	General Farming	Less reliable sensors used

	temperature, and relative humidity, Relay			
[38]	Soil Moisture	IoT, ML	General Farming (prototype)	Remote sensing image requires image enhancement for precise operation
[40]	Soil Sensors	IoT	Agriculture Water Management	The sensor needs to be corrosion-free.
[94]	Camera	IoT & ML	Smart Agriculture	Quality of crop images is a critical issue
[95]	Arduino Uno	IoT	Farming	Large data are difficult to consider.
[98]	Not Applicable	IoT & ML	Crop Prediction	The precision farming system is not developed.
[101]	Not Applicable	IoT & DL	Data Analytics	The decision making model is not implemented.

2.3 SUMMARY OF THE REVIEW OF LITERATURE

In this chapter, we have analyse the subsequent data for the precise greenhouse management system. A smart greenhouse system, obsessed with market demands and dependent on improvement plan, is an amalgamation of IoT with agriculture.

It is crucial to have a high level of technical expertise and technical involvement while observing and managing the greenhouse climate. The meticulous data was distinguished and empowering their full consideration to characterise the whole investigation as per their restriction and the likelihood of work enhancement.

According to the research gap, agriculture and its repercussions are influenced by a number of fundamental components and circumstances. Cultivators in traditional greenhouses can manage ecological parameters through a relative control component that includes manual interpolation, resulting in energy and productivity losses, as well as higher labour costs on a regular basis.

From the above study, there are some major research gaps that should be taken into consideration for system improvement.

1. Less parameters are taken into account.
2. Practical implementation can be an issue.
3. Low reliability.
4. Low scalability.
5. Latency should be considered.
6. Lack of effective storage mechanism.
7. Less reliable sensors are used. Etc.

To overcome these challenges, an intelligent greenhouse weather detecting and controlling system emerges to liberate. IoT with Artificial Intelligence (AI) is becoming more widely used, which is a key aspect in the development of a smart precise greenhouse framework in the future.

CHAPTER 3 DEVELOPMENT OF IoT BASED SMART FARMING SYSTEM

3.1 Overview

The chapter describes the proposed Smart Farming System for Data Analytics (SFSDA) Using ML Enabled Internet of Things. The proposed system will be divided into four layers for better understanding. The cloud layer, fog layer, edge layer, and sensor/device layer are four fundamental architectural layers for a precision-controlled greenhouse management system. This chapter is more likely to focus on sensor/device layer which will be used for precise data collection from the field. In this a hardware prototype is developed to collect all information about the greenhouse environment including temperature, humidity, CO_2, soil moisture, and light intensity. For data collection, various sensors and techniques have been implemented, which are explained in detail in this chapter.

3.2 Block Diagram

Figure 3.1 shows the suggested paradigm for an intelligent farming system to be used in the greenhouse. The detail working of the figure is explained in the following.

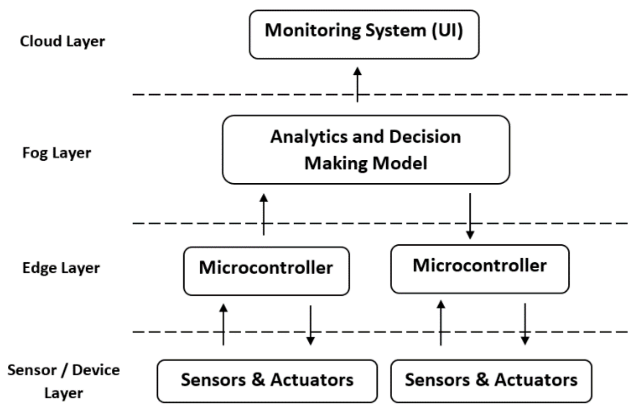

Figure 3.1 Smart Farming Infrastructure for Greenhouse Management

3.3 Working

The sensor layer is where all the field environment-related sensors and actuators live. The edge layer typically comprises a controller unit to which various sensors and actuators are connected in order to collect data for transmission to the fog layer. The primary function is to create an analytics and decision-making model using edge-level data and to provide actuator control signals to the edge layer. Finally, the upper cloud layer provides a UI dashboard that displays a graphical representation of sensor and actuator data. The proposed framework is unique in that it uses the Internet of Things (IoT) to aid farmers with greenhouse management. It is all done remotely so that farmers can monitor and adjust factors such as soil moisture, CO_2, light, and temperature from afar. Because of this, farmers cannot physically go check on their crops.

3.3.1 Sensor Layer

The greenhouse, which is used for this experiment, is very climate sensitive and the plants being investigated are Gerbera daisies and broccoli. Various sensors like light, gas, temperature, humidity and moisture are deployed to track overall conditions in a green shade by using actuators like pump, fan and light. In addition, to relay parameters and run equipment such as fans and pumps, actuators will be chosen and employed. The adoption of a greenhouse management system provides several benefits to crop and disease control.

3.3.2 Edge Layer

The nodes and edges, which are sensors, are deployed in the field and linked to a low-power microcontroller optimised for the Internet of Things. In this research, we used an MCU Node ESP 32 to collect and process sensor data and send it to the upper layer's home base. Calibration and verification of sensors against an expected value are necessary for accurate data collection in analogue or digital form. To guarantee crop survival through precise crop management, it is necessary to gather data for both favourable and unfavourable climatic factors.

3.3.3 Fog Layer

Decisions, edge layer control, and data communication to the cloud layer for farmer use are the key responsibilities of this layer. The complex decision-making system is the result of an ML algorithm. The functions of fog layer include:

- Information is produced by sensors in the boundary layer.
- Real-time or batch data collection enabled by sensors included in IoT devices (temperature, humidity, camera vision, light intensity, etc.).
- Acquiring and compiling information into a single database.
- To clean and fix the data, algorithms might be used throughout the filtering process.
- The function of the data should be taken into account while classifying it.
- **Computing:** This stage entails performing computations on the categorised data (e.g., the amount of water to pump).
- Prediction-based decision making and data visualisation through reports and dashboards.

3.3.4 Cloud Layer

Adafruit IO Cloud will be used to display data from all edge nodes before it is sent to the base station for processing and management. A graphical user interface (UI)-based programme allows farmers to monitor the growth of their crops. A server-less execution environment for constructing and linking cloud services is called cloud functions. You can create straightforward, one-purpose functions with cloud functions that are linked to events released by your cloud infrastructure and services. When an event being watched fires, your function is called. In a completely managed environment, your code runs. Neither server management nor infrastructure provisioning is required.

Data can be used by a system called Adafruit IO. It emphasises simplicity of usage and permits straightforward data connectivity with minimum need for scripting.

The Adafruit IO offers an easy-to-use platform for data analysis. The MQTT client libraries are included with IO.

3.4 Data Acquisition using an Experimental Model

For the new purpose of testing the suggested greenhouse system, a prototype experimental model was developed using an embedded system device that contains various sensors, as illustrated in Figure 3.2.

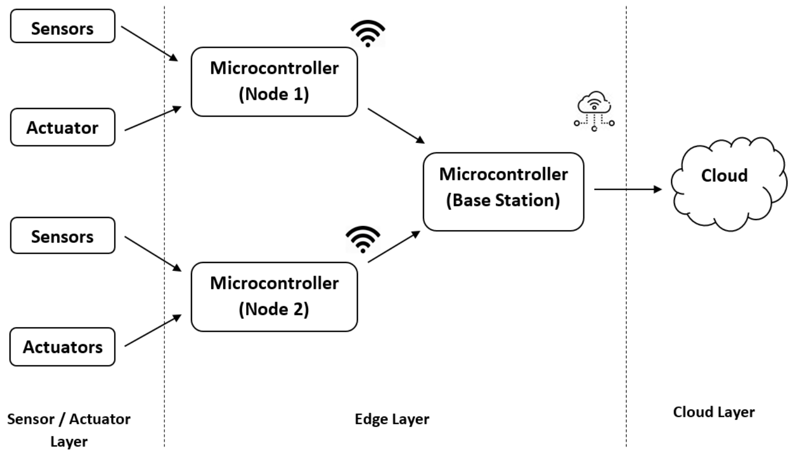

Figure 3.2 Proposed System for Data Acquisition

3.4.1 Sensors and Actuators

In the proposed prototype, four sensors, DHT11, LDR, MQ2, Cu Leads, are used in experimentation with actuators fan, light and pump. The DHT11 temperature sensor is used which can also detects humidity, the LDR is used to detect the light intensity inside the greenhouse, the MQ2 sensor detects CO_2 levels for day and night inside the greenhouse, and Cu leads well be utilized for sensing soil moisture inside the greenhouse. The actuators will be controlled by the control signal generated by the intelligent control system. Gerbera daisies and broccoli are two of the crops studied in the suggested model. Gerbera and Broccoli are two different flowers that have different characteristics and both require a separate atmosphere for their growth. All the data required for the development of gerbera and broccoli were collected from the project in-charge of Hi-Tech lab of Agriculture University, Pune. The questionnaire is made to solve all doubts about gerbera and broccoli and it is being validated by experts.

3.4.2 Embedded System

As shown in Figure 3.3, all of the sensors required to collect the greenhouse parameters are wired to a microcontroller Node MCU ESP 32. Various parameters are logged in serial fashion on a personal computer, with time stamp values of 1 hour. Adafruit's IO cloud platform uses the MQTT protocol to continuously monitor temperature, humidity, light intensity (using the LDR sensor), carbon dioxide (using the MQ2 sensor), and soil moisture (using the Cu Leads) for 15 days, day at 11.00 am and night at 09.00 pm, at regular intervals in the month of December of 2021 year. 30 data samples have been collected to send over cloud using microcontroller for training the data.

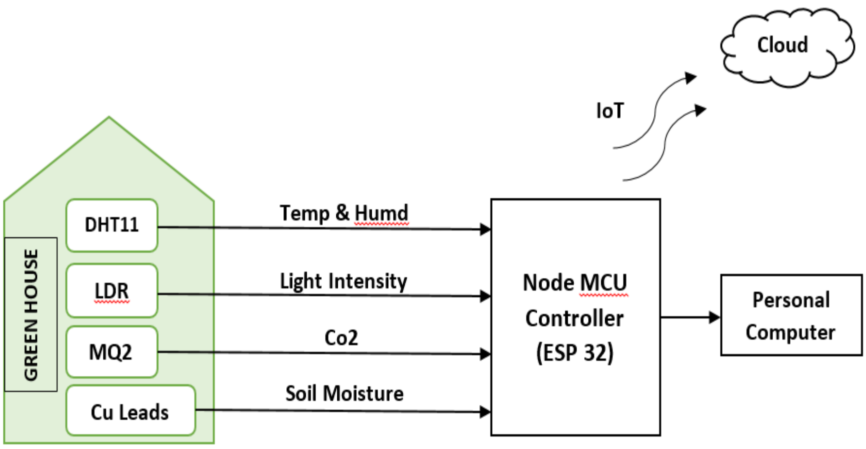

Figure 3.3 Proposed Experimental Model

3.4.3 Message Queuing Telemetry Transport (MQTT)

The data privacy and integrity are protected via MQTT, a lightweight publish-subscribe system that uses the TCP/IP network. A message broker is an intermediary in the MQTT protocol that facilitates communication between message senders and recipients. It is possible to use the same client to send and receiving alerts. Each letter represents a different subject area. The topic is the string that contains the slashseparated levels of the message hierarchy for routing. When a customer registers interest in a certain topic area, the broker will send them any messages that pertain to that area. Smart sensors, wearables, and other Internet of Things (IoT) devices typically have to transmit and receive data over a resource-constrained network with limited bandwidth. These IoT devices use MQTT for data transmission, as it is easy to implement and can communicate IoT data efficiently.

MQTT supports messaging between devices to the cloud and the cloud to the device. MQTT implementation requires a minimal amount of code that consumes very little power in operations. The protocol also has built-in features to support communication with a large number of IoT devices. In addition, wildcards allow you to subscribe to many topics at once. The transfer of data from temperature sensors in a greenhouse system is shown in Figure 3.4.

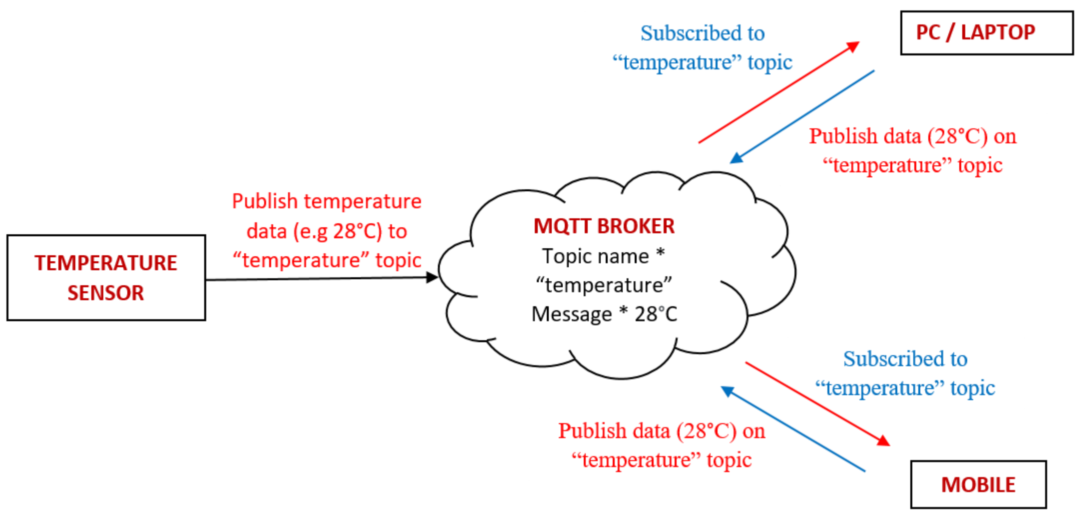

Figure 3.4 Workflow of MQTT for sensor data

The MQTT protocol has the following advantages, which have led to it becoming a standard for IoT data transmission.

i. Lightweight and efficient

The lightweight and efficient MQTT implementation of the IoT device uses little resources, making it suitable for even modest microcontrollers. A simple MQTT control message, for instance, needs just to include two data bytes. For maximum efficiency, the MQTT protocol uses compact message headers.

ii. Scalable

Minimal code with low power consumption is all that is needed for a scalable MQTT implementation. The protocol was designed with features already included to facilitate interaction with a wide variety of IoT gadgets. It provides easy access and transfer of data without disturbing the runtime process. Therefore, the MQTT protocol can be used to establish a network connection to potentially millions of such devices.

iii. Reliable

Connectivity for many IoT devices occurs through slow and laggy cellular networks. Built within MQTT are features that speed up the time it takes an IoT device to reconnect with the cloud.

iv. Secure

Using contemporary authentication protocols such as OAuth, TLS1.3, Customer Managed Certificates, and more, Secure MQTT makes it easy for developers to encrypt messages and authenticate devices and users.

v. Well-supported

The MQTT protocol is widely supported by a number of languages, including Python. Therefore, it can be integrated into virtually any application with little effort from the programmer.

The publish/subscribe paradigm is fundamental to the MQTT protocol's operation. Clients and servers have always had direct contact in conventional network architectures. Clients make requests for information or data from the server, which are then fulfilled. However, with MQTT, the sender and the recipient of messages are separated via a publish/subscribe structure. Instead, a third party, known as a message broker, is in charge of facilitating interaction between content creators and consumers.

The broker's responsibility is to sort the messages arriving from the publishers and deliver them to the relevant recipients. Below is an example of how the broker separates the publisher and the subscriber.

i. Decoupling in space

The publisher and the subscriber do not know the other's IP address or port number, and neither knows where the other is located on their respective networks.

ii. Time Decoupling

Both the publisher and the subscriber are not active or connected to the network at the same time.

iii. Synchronisation Decoupling

The sending and receiving of messages from both publishers and subscribers is completely asynchronous. The subscriber can receive messages independently of the publisher.

By creating clients and brokers with the following core components, MQTT realises the publish/subscribe concept.

i. MQTT Client

Any machine, from a server to a microcontroller, with the MQTT library installed is considered a MQTT client. The client is a publisher if it is the one doing the message sending, and a subscriber if it is the one doing the message receiving. A device that uses MQTT for networked communication is known as an MQTT client.

ii. MQTT broker

The MQTT broker is the back-end system responsible for coordinating communications between clients. The broker's job is to receive messages, sort them, determine which clients have subscribed to each message, and then deliver them to those clients. Among the other things it is responsible for are:

- Authorising and authenticating MQTT clients
- Sending data to a remote system for processing
- How to deal with missing client sessions and communications?

iii. MQTT Connection

The MQTT connection between clients and brokers is established, and communication begins. Sending a CONNECT message to the MQTT broker begins the connection establishment process on the client side. By sending a CONNACK message, the broker verifies that the connection has been made. A TCP/IP stack is needed for communication between the MQTT client and the broker. Customers only communicate with the broker, never with each other.

3.4.4 Adafruit IO Cloud Platform

Adafruit IO provides a cloud platform for monitoring sensor data and observing the actuator controls. Adafruit IO is a cloud service to which our edge devices are linked. Its primary use is to store and then displaying data from controllers that belong to edge layer to which sensors attached. The sensor data are analysed to control the actuator using an intelligent system deployed at the fog layer and the status of actuator device control on the/off is visualised on Adafruit cloud platform.

This platform can be used to:

- Display the generated data online in real time using graphs and squares on a dashboard.
- In-dash buttons that may be used through the internet or a mobile device to remotely activate and deactivate devices (motors, sensors, etc.).

- Integrate your work with online tools like RSS feeds, IFTTT, email, etc.
- Implement threshold- and time-based triggers to take action when the data values meet or exceed predetermined conditions.

One such cloud service, Adafruit IO, is geared towards IoT deployments. The Adafruit IO is compatible with several development boards and microcontrollers. Adafruit IO is preferred by IoT developers over other IoT cloud platforms because:

- There is robust support for user interfaces and a variety of programming languages provided by the API.
- Better judgements may be made with the help of data visualisation tools like the dashboard.
- Confidentiality - More advanced encryption methods are used to keep data safe in the cloud.
- Many blogs with phenomenal community support enable continuing product enhancements.

3.5 Flowchart

The technique and workflow of the proposed system are depicted in Figure 3.5. When the system starts, it will initialise all the sensors that we are using for data collection. All sensors will measure the agriculture field data and send it to the microcontroller.

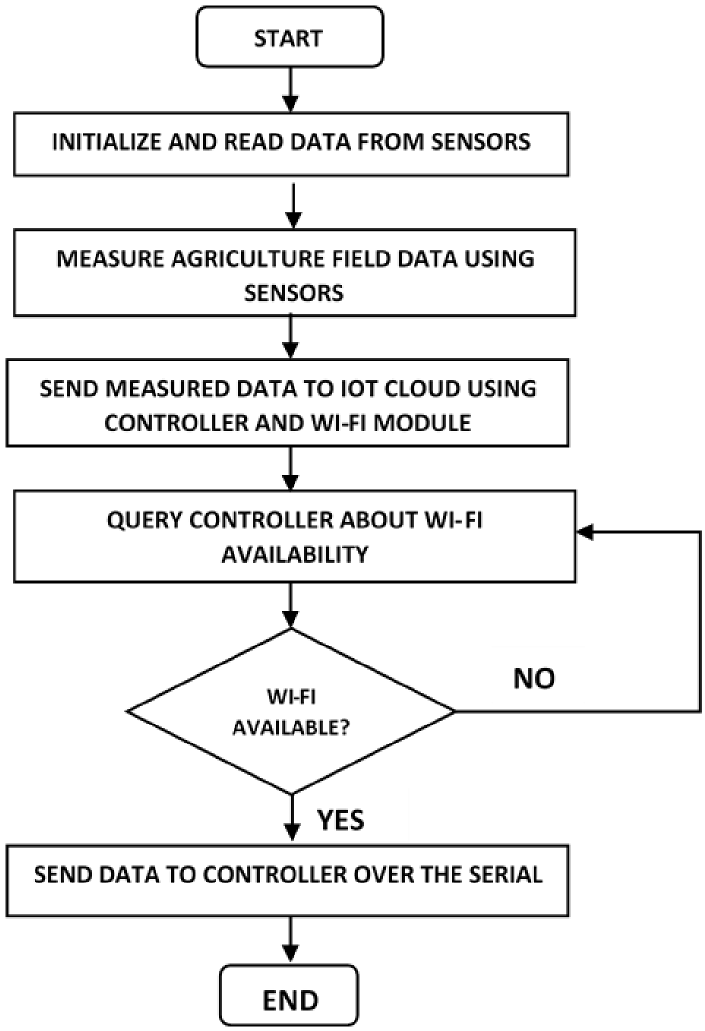

Figure 3.5 Workflow of Experimental Model

The data received by the microcontroller will be sampled and converted in a suitable format before sending them to the cloud. For sending the data to clouds, the Internet needs to be active. So, controller will ask for the WI-FI availability, and if the WI-FI is available, then data will be sent to the clouds otherwise controller will ask for the WI-FI availability until the WI-FI is not available. The next data set will be collected after the set interval and the same process will continue.

3.6 Data Acquisition, Monitoring, and Interpretation

Figure 3.6 shows the results of the prototype tests conducted using the proposed experimental design, which represented two crops produced under contrasting conditions. One, building a sensor net for intelligent green-house monitoring; two, automating actuators; and three, designing core model-embedded systems for plant growth and feeding were the three primary stages of testing. Using an embedded system, the proposed technique successfully evaluated soil moisture, temperature, CO_2, and plant light which are all critical elements in the successful operation of a greenhouse.

Figure 3.6 Experimental test bench.

Figure 3.7 displays the results of our serially transmitted measurements from several experimental setups. All of this sensor data could be monitored in real time over the Internet on the Adafruit IO Cloud dashboard after being published from the nodes to the Adafruit broker. Arduino programming is used to collect and send data to adafruit IO. Farmer can monitor the data over serial monitor using an arduino. For display purpose a prototype is set with less delay to have a proper understanding of sensor working. The real-time data collection is achieved by the system as observed on serial computer.

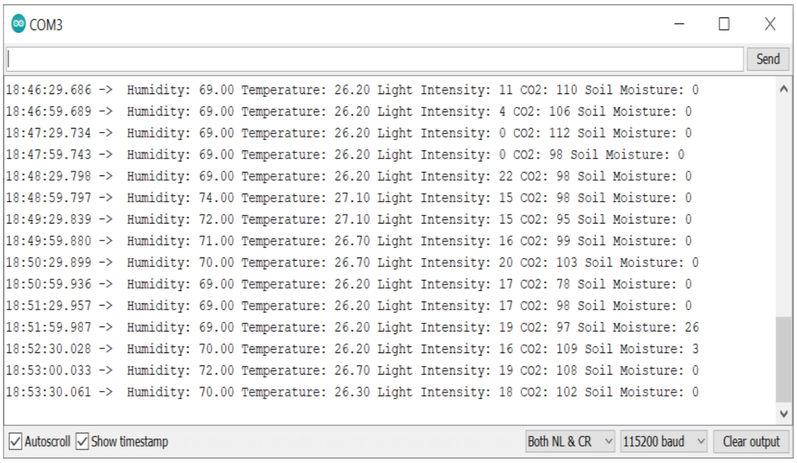

Figure 3.7 Observed sensor data on a serial display alongside accurate time stamps.

The prototype was first tested in a living room before visiting the farm field. Hence it is observed in the serial monitor that humidity, temperature, light intensity, and CO_2 have some values, but the moisture level is showing the 0 value on the monitor. The user can access the sensor data for monitoring purposes by subscribing to the Adafruit IO system. The prototyped has been developed with two separate nodes for data collection inside and outside of the greenhouse. The two nodes, i.e., Node 1 and Node 2 have been created for the better understanding of the output data. Figures 3.8 and 3.9 demonstrate how the user could subscribe to this information and have rapid access.

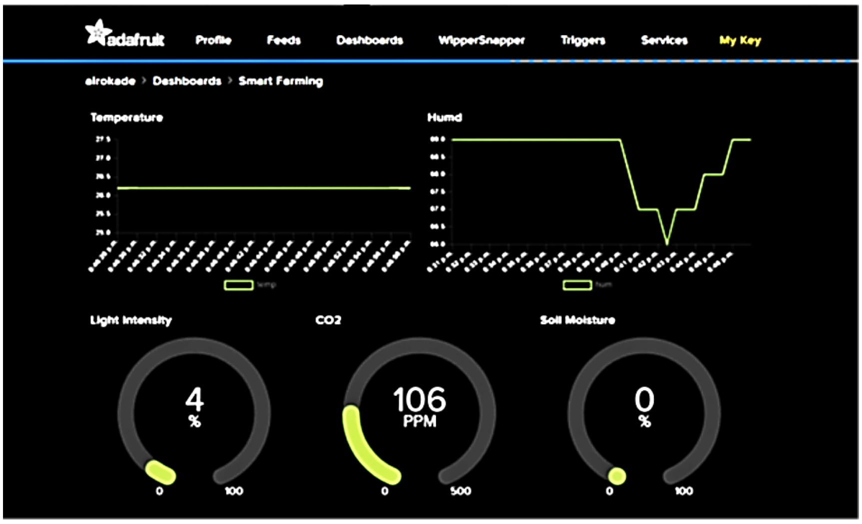

Figure 3.8 For Case 1, sensor data was shown on Adafruit's IO cloud dashboard.

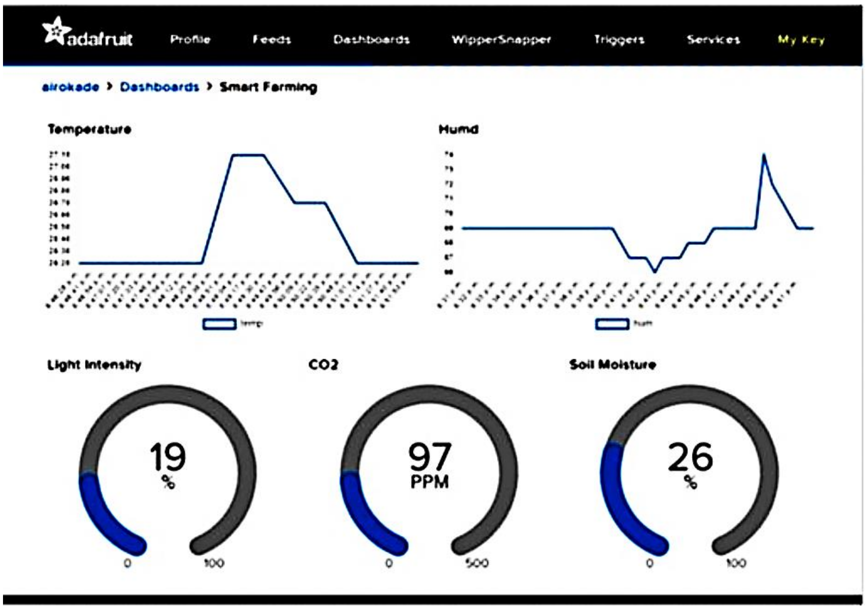

Figure 3.9 For Case 2, sensor data was shown on Adafruit's IO cloud dashboard.

For better understanding two different themes have been chosen for Node 1 and Node 2. Node 1 graphical data interface uses the dark theme in which one can observe the changes in all parameters of the system. Node 2 uses the white dashboard for sensors inside the greenhouse for the interface to show changes in data.

Figure 3.10 shows the graph for the reference data for broccoli and gerbera and the sensor data collected by various sensors. Reference data are validated from the university experts and the reference book for differentiating with actual data.

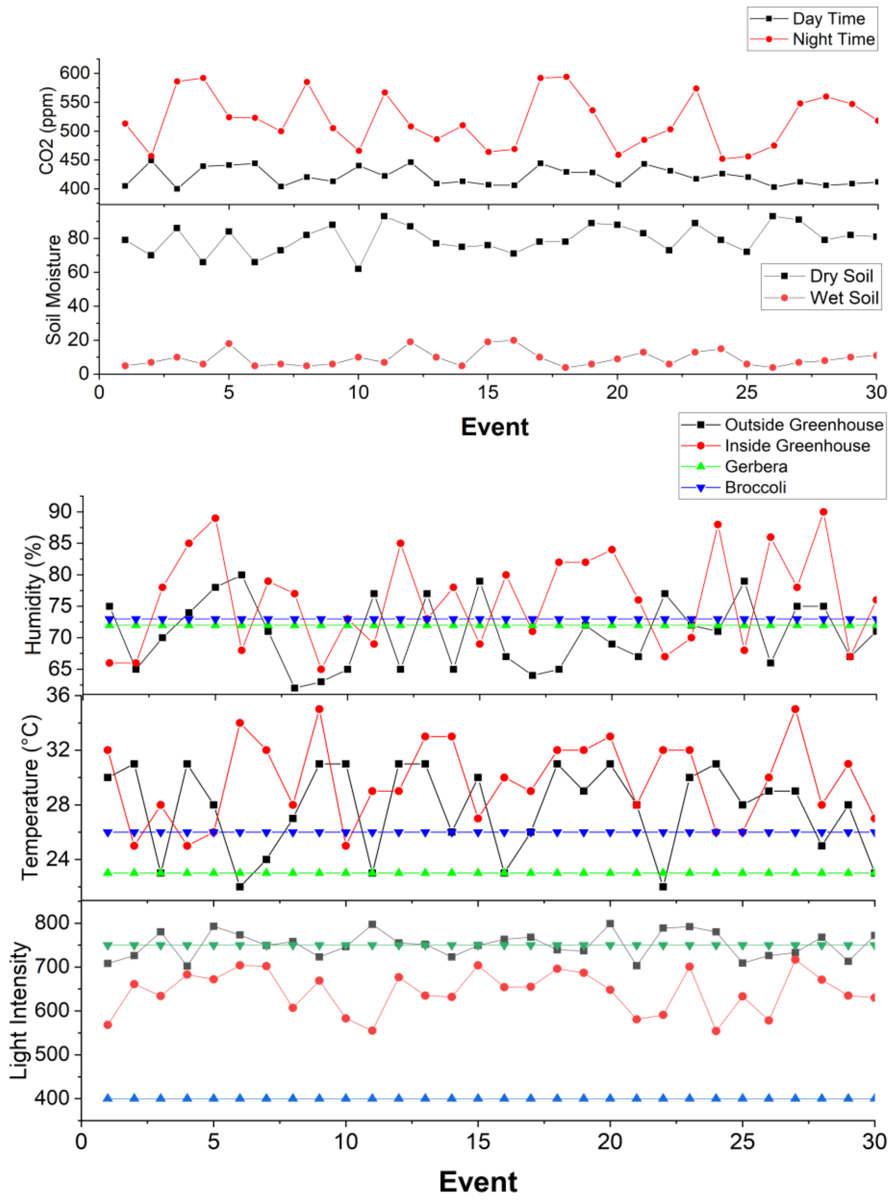

Figure 3.10 Gerbera and Broccoli both have different sensor parameter representations outdoors and within the greenhouse.

Soil moisture levels can be taken into account by rolling up or down the greenhouse's doors and windows. To keep the plant cool and promote rapid development, photosynthesis is dependent on a higher concentration of carbon dioxide

(CO_2) and a higher water level in the evening than during the day. By absorbing CO_2 during the day and releasing it at night, the greenhouse can keep the CO_2 content at its highest throughout the night, as shown in Figure 3.10.

The soil moisture level is crucial because too much water can cause the plant to get a fungal infection and not enough water can dry out and kill the plant. Consequently, it is essential to pay close attention to the plant's watering needs. Because photosynthesis occurs primarily at night, plants require more CO_2-rich water. As can be seen in Figure 3.10, the plants were completely submerged when the soil moisture sensor returned a negative number. A DC motor controlled the automated closing of the greenhouse's windows and doors.

For example, in Figure 3.10, a positive number meant that the soil was dry and that it needed to be rewetted. The temperature inside the greenhouse is crucial, and thus it needs to be kept as high as possible. Warmth promotes flowering, fruiting, photosynthesis, and seed germination.

Compared to the range outside the greenhouse, the relative humidity and the temperature range inside the greenhouse were therefore kept as close to ideal as feasible. Plants employ a variety of different systems, but one that is crucial to development, blooming, and overall form is the photosynthetic system, which benefits from the Sun’s spectrum of colours.

For too dry or too wet soil, you can open or close the greenhouse's windows and doors. Photosynthesis, the process by which plants obtain their energy from carbon dioxide and water, is most effective when carried out at night rather than during the heat of the day. After measuring the level of CO_2 concentration in a greenhouse, the maximum CO_2 level is maintained overnight because the greenhouse absorbs CO_2 from day to night. Figure 3.10 shows this daily decline in CO_2 levels as a result of photosynthesis.

The amount of water in the soil controls whether the engine will run, as shown in Figure 3.10. Both the inside and outside of the greenhouse are displayed graphically, and the actuator fan or humidifier is adjusted correspondingly. Figure 3.10 shows that adequate light for photosynthesis is needed both inside and outside the greenhouse; therefore, artificial lighting is adjusted accordingly. Therefore, the amount of light entering the greenhouse was restricted to a level comparable to that that would normally enter the greenhouse on a cloudy day.

The experimental data is collected for three different seasons to understand the best suitable climate conditions for gerbera and broccoli. The average 90-day data has been collected and validated with reference data collected for gerbera and broccoli. Some of the data samples are collected at day and some are collected at night for random data generation and to get the precise results in extreme worse conditions. The nonlinear data generation will always lead the algorithm to work smoothly in a complex situation. The result graphs show the data representation for CO_2 for day and night time, soil moisture for dry and wet soil, Humidity, Temperature and light intensity for inside and outside greenhouse. The data collection is done for hot weather season (summer), monsoon season (rainy) and cold weather season (winter).

The results for various seasons for different parameters are shown in Figure 3.11 to figure 3.13. The climate conditions in the study region are tropical wet and dry, with hot, dry summers and mild to cool winters. Winter lasts from November to March, the monsoon season from July to October, and the summer season from March to June. The test field region, which is 0 feet (0 metres) above sea level, experiences tropical wet and dry seasons. The district's average annual temperature of 30.63°C (87.13°F) is 4.66% higher than the national average for India. The test field area normally has 103.26 wet days (28.29% of the time) annually and receives approximately 120.15 millimetres (4.73 inches) of precipitation on average. The maximum temperature observed is 47 ° C and lowest is 24.03 º C. Figure 3.11 shows the sample data collected at day and night in the summer season.

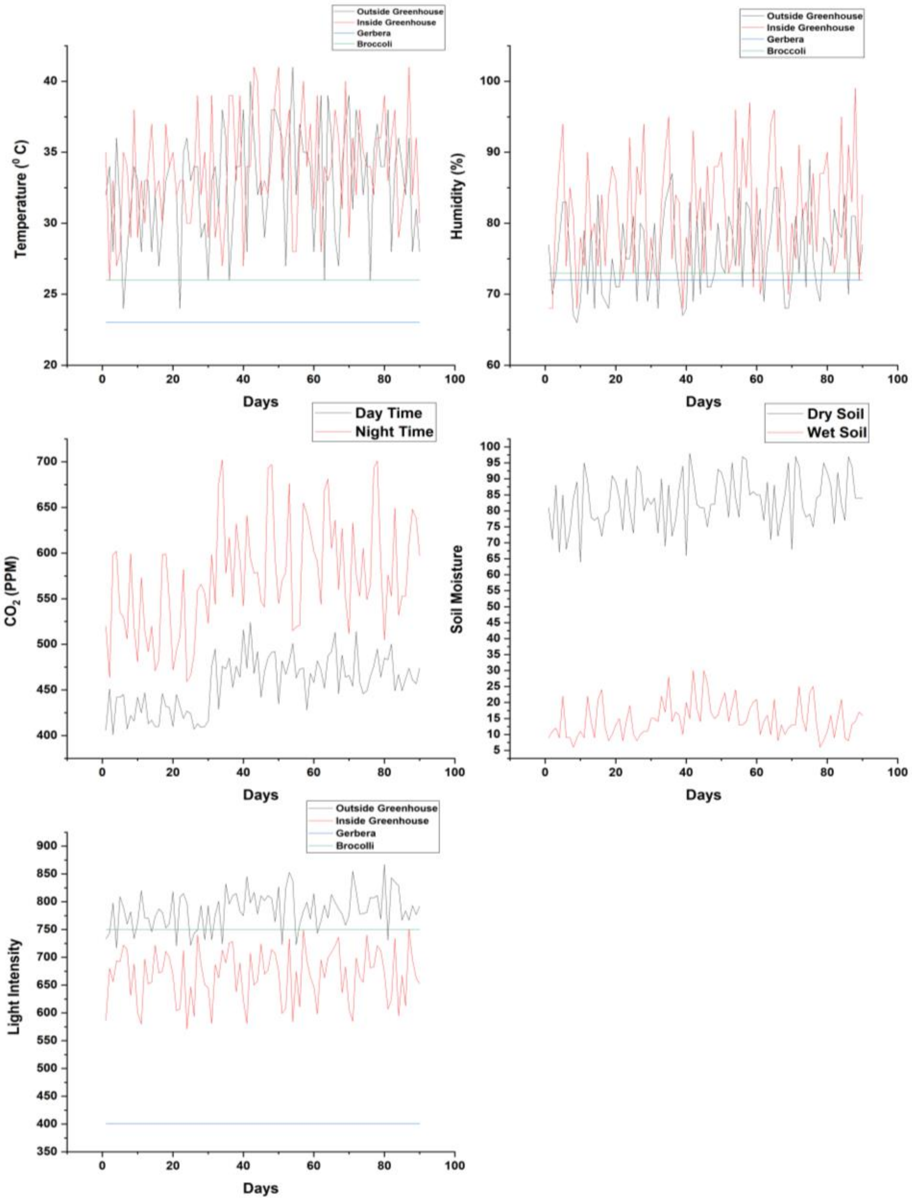

Figure 3.11 Sensors reading in summer season for greenhouse monitoring.

Similarly, data collection is processed for the rainy season for all the five parameters inside the greenhouse comparing the reference data of gerbera and broccoli with the actual data in Figure 3.12.

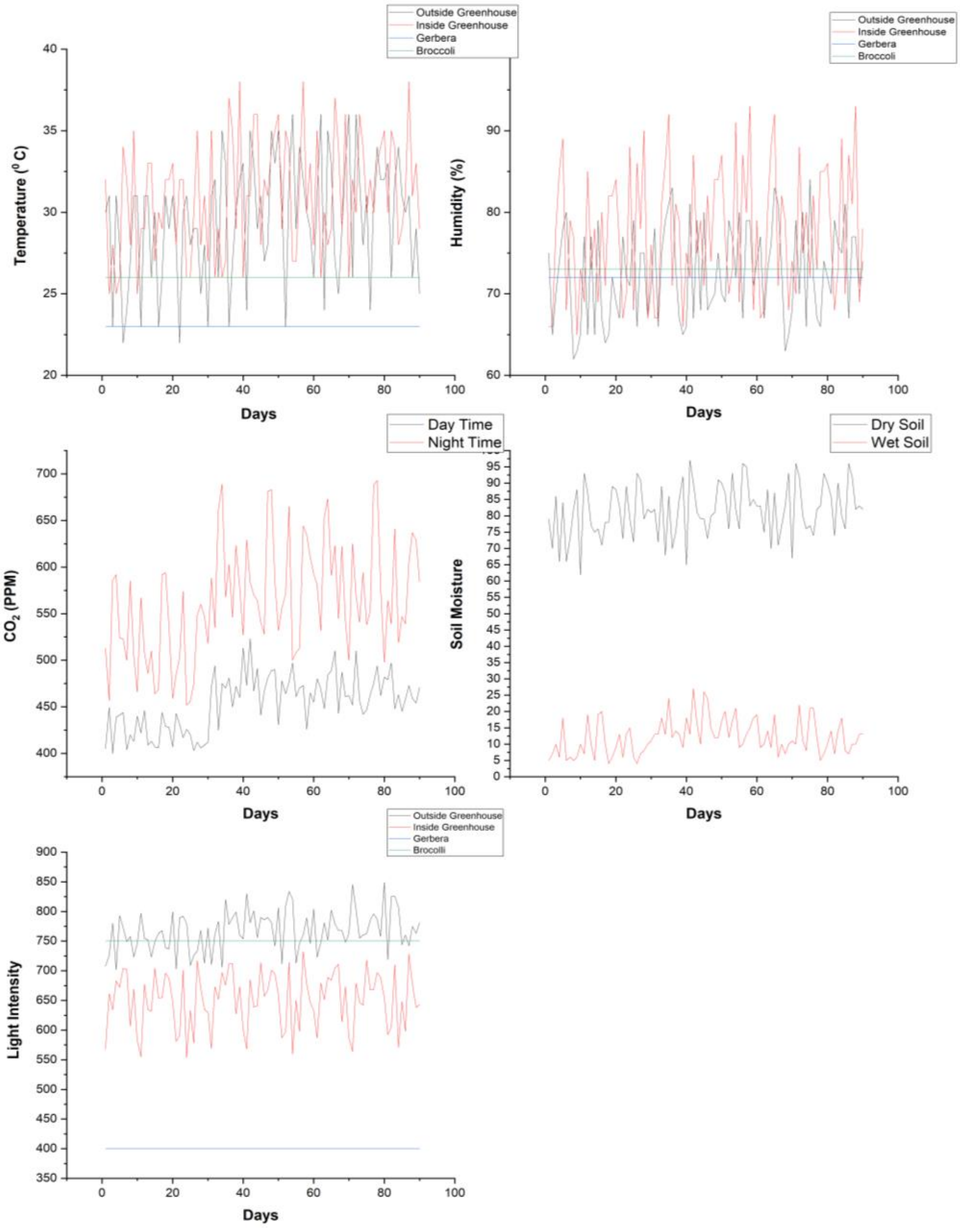

Figure 3.12 Sensors reading in rainy season for greenhouse monitoring.

As seen in the graph, the temperature of the greenhouse is quite low at night and high at daytime. It will require much more data monitoring and parameter control during the season as the temperature requirement for both gerbera and broccoli is low for both day and night. The data collection for the winter season is done by using the same parameter that is shown in figure 3.13.

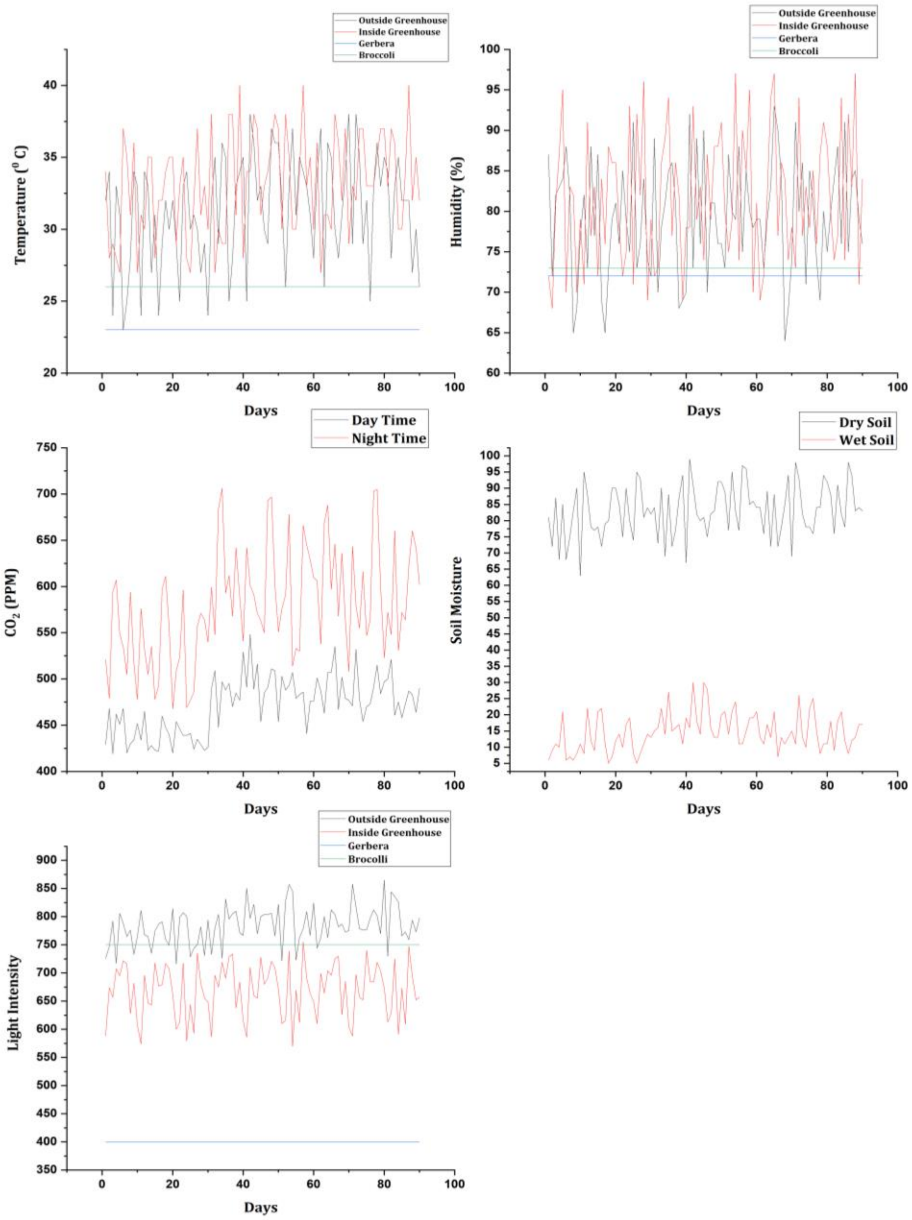

Figure 3.13 Sensors reading in winter season for greenhouse monitoring.

The graphs conclude that the winter season is the best among all to have the cultivation of gerbera and broccoli. The research works for the cultivation of crop in any season using a greenhouse management system and by applying ML algorithms to control the atmosphere of the greenhouse for the smooth development of the crop.

3.7 Summary of the Chapter

- The proposed four-layer architecture is covered in this chapter, along with the importance of each layer in the development of an Internet of Things (IoT)-based smart farming system.

- The main objective of this framework is to develop a prototype system for smart farming that accounts for the greenhouse environment, monitors greenhouse plant activity using a variety of cloud-based sensors, and visualises the data using data interpretation. It can be concluded that the IoT Based Smart Farming System (IBSFS) for data collection through various sensors has been successfully developed.

- The Data Collection of various factors for analysing has been carried out by using a proposed prototype, which shall be further compare with reference data for validation.

- All data sample will be stored for performing different machine learning algorithms for effective decision making which will be helpful in achieving precision management of a greenhouse.

CHAPTER 4 ANALYTICS AND DECISION-MAKING MODEL USING ML FOR PRECISION MANAGEMENT

4.1 Overview

This chapter depicts the proposed approach established at the third layer of our proposed model, i.e. a fog layer for a data analytics system employing various ML methods. The two machine learning algorithms were chosen because of their theoretical and implementation advantages, which perfectly suits the system dataset to get the intelligent and precise output. The classification and regression techniques were adopted and analysed in this chapter to get the expected results. The proposed system used classification and regression algorithms which were based on supervised learning data instead of unsupervised learning approach, as while experimentation, the system was monitored and the data behaviour of both sensors and actuators was observed. Also, supervised classification tends to be more accurate and is commonly used when labelled data is available. The actual data and expected data are compared for both two techniques. The system is developed to control the actuators devices like pump, fan, and light within the greenhouse making the greenhouse a smart one.

One of the most well-liked supervised learning algorithms, Support Vector Machine, or SVM, is used to solve classification and Regression problems. It works well for many real-world issues and can solve both linear and nonlinear problems. Text classification, picture classification, spam detection, handwriting recognition, gene expression analysis, face detection, and anomaly detection are just a few of the tasks that SVMs can be used for. SVMs can handle high-dimensional data and non-linear relationships, making them flexible and effective in a wide range of applications. The optimal hyperplane selected to divide the two classes in this supervised machine learning issue.

A neural network known as a multilayer perceptron learns the correlation between linear and nonlinear inputs. A perceptron is a basic form of neural network that has the ability to categorise patterns that may be separated linearly. It has a single layer of binary output and weighted inputs. A more sophisticated kind of neural network called a multilayer perceptron (MLP) is capable of learning to categorise nonlinearly separable patterns. It effectively manages large volumes of input data. Following training, quickly makes predictions. Even with fewer samples, the same accuracy ratio is still possible. The feed forward neural network is supplemented by the multilayer perceptron (MLP). The input layer, output layer, and hidden layer are the three different kinds of layers that make it up.

The training and testing of data is performed using MATLAB 2021 version. The accuracy, sensitivity, specificity, latency, f-score, and LMSE are calculated and observed in this chapter. The detailed description is given below.

4.2 Block Diagram

The suggested methodology for data analytics systems using ML algorithms, typically regression modelling, is illustrated in Figure 4.1 and is addressed in more detail in the following.

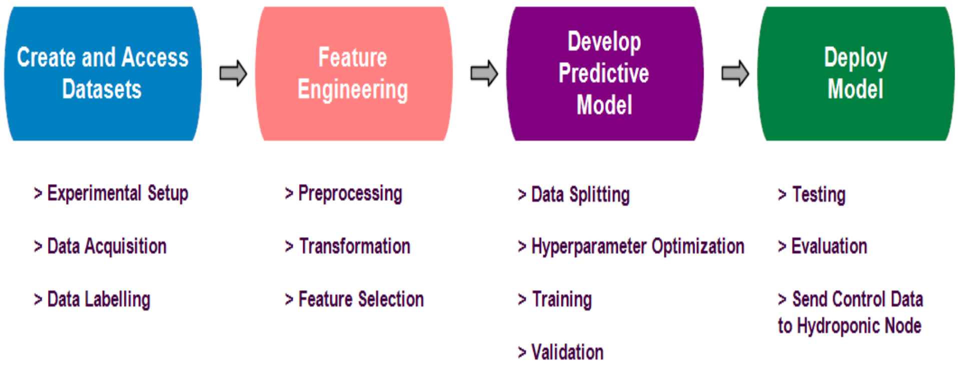

Figure 4.1 Implementation Flow of Data Analytics System

At first, data from sensors is generated at the edge layer and then acquired. Information gathered by Internet of Things (IoT) devices, especially sensors, which can gather information in real-time or in tiny batches (temperature, humidity, camera vision, light intensity, etc.). In a target database, data are collected and combined. Pre-processing is the cleaning and editing of stored data. Data categorisation based on the classifier's initialisation and validation after ML methods have been trained in order to save the generated model. On the categorised data, calculations will be made during the prediction phase (for example, when to pump water). Decision-making based on predictions and data visualisation through reports or dashboards. For implementation purposes, the Support Vector Machine and the Multi-Layer Perceptron Neural Network are specifically two ML algorithms that were chosen.

4.3 Working Principle

4.3.1 Create and Access Dataset

To train a model using a dataset generated in an experimental context, the ML approach divides the data into train and test sets, each with its own output data label. Overfit may be avoided with the use of data splitting, which is widely used in ML. When an ML model fits the training data precisely but fails to predictably fit fresh data, we say that the model overfits. Raw data used in a ML model is often split into half. With a 70:30 split between training and testing, 70% of the data is used to fine-tune the model and 30% is used for validation. Each sensing parameter in the sensor data has a total of 1024 samples.

4.3.2 Feature Engineering

"Feature engineering" is the process of identifying features from unstructured data using data mining tools and domain knowledge. These traits can be incorporated into ML algorithms to improve their performance. You might think of feature engineering as a type of applied ML. Improved model accuracy on unseen data is another byproduct of this process, which entails translating raw data into characteristics that more accurately describe the underlying problem to the prediction models.

There are two main objectives in feature engineering:

- Creating a suitable input dataset that meets the requirements of the ML algorithm;

- Increasing the utility of ML models.

All raw data are given in *.csv format, which may be read using the Matlab programming language. This method is useful for gathering information and using ML regression strategies. By choosing and combining features from many datasets to generate a smaller feature subset, feature extraction is a technique for discovering previously unknown features. Selecting features from a dataset is the last step in the ML process; these characteristics form the basis for subsequent operations like clustering, classification, etc. You can get there with the use of techniques such as univariate analysis, correlation analysis, and so on. Our method employs univariate feature selection, a technique for choosing the most useful characteristics through a single statistical measure.

4.3.2.1 Pre-processing

Data pre-processing techniques like resampling, normalisation, noise filtering, attribute selection, etc., aid in increasing the precision of intelligent algorithms' categorisation or estimate. The feature samples in the data set are first normalised and scaled according to industry standards.

The standard scaler, to standardise data, adheres to a specific concept of standardisation. When features are standardised (also known as Z-score normalisation), they are rescaled so that they exhibit the characteristics of a normal distribution with mean and standard deviation equal to zero and one, respectively. The following is how standard sample scores are calculated—also referred to as z scores.

$$z = \frac{x - \mu}{\sigma} \quad \ldots\ldots\ldots (1)$$

When characteristics follow a Gaussian distribution but have different means and standard deviations, standardisation can help by transforming them into a normal Gaussian distribution with those values fixed at 0 and 1. Linear regression, logistic regression, and linear discriminate analysis are examples of methods that benefit from having their input variables rescaled to fit the Gaussian distribution. Remove the mean and scale the features to a variance of 1 to get a standardised set. Centering and scaling are carried out independently on each feature by computing the necessary statistics on the samples in the training set. Once the data has been transformed, the mean and standard deviation are kept for future use. Since many ML estimators behave abruptly if the features do not nearly resemble normally distributed data (such as Gaussian with zero mean and unit variance), a dataset must be standardised in order for them to work properly.

When the values are normalised, they are moved and rescaled so that they fall into the range of 0 to 1. In other words, it is a form of Min-Max scaling. The normalisation formula is as follows:

$$\mathcal{X}' = \frac{\mathcal{X} - \mathcal{X}\min}{\mathcal{X}\max - \mathcal{X}\min} \quad \ldots\ldots\ldots\ldots (2)$$

The maximum and lowest values of the feature are denoted here by Xmax and Xmin. If X has the lowest value in the column, then X' has a numerator of zero. However, if X is the highest number in the column, then X' equals 1 because the numerator and denominator are both 1. X' is between 0 and 1 if and only if X is between the lowest and maximum values.

4.3.2.2 Feature Selection

The reduction in predictive analysis is achieved by a process known as feature selection. The concept of "garbage in-garbage out" applies to ML, which means that the input data must be carefully scrutinised.

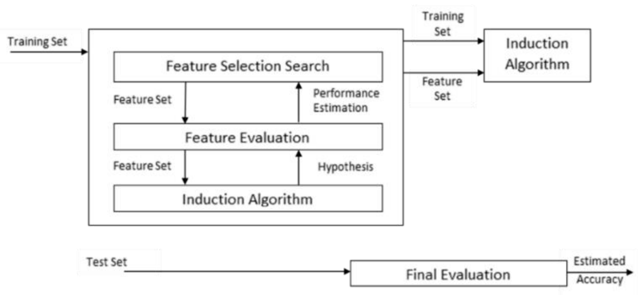

Figure 4.2 Feature selection strategies

To assign scores to subsets of variables based on their prediction capacity, the Wrapper technique treats the target learning machine as a black box. Figure 4.2 shows the induction process used in supervised ML, where a collection of training cases is shown, each of which is defined by a vector of feature values and a class label. An effective classifier is induced using the induction algorithm, which is sometimes called a black box. The feature subset selection method is a "wrapper" around the induction process in the wrapper technique. The large number of calculations needed to produce the feature subset is a major downside of this method.

Feature selection methods streamline ML models to make them more accessible to scientists. The major impacts of the curse of dimensionality are mitigated by IT. Additionally, by increasing the model's generality, this method helps alleviate the issue of overfitting. As a result, the algorithm's computing time and space requirements are reduced, and its predictive performance is enhanced.

The advantages of feature selection include: increased accuracy in classification and prediction, accelerated training, and reduced space requirements, enhancement of domain interpretability and comprehension.

4.3.3 Develop Predictive Model

Features from both the training and validation sets will be required to evaluate the model's efficacy. The model is then trained using a mix of the SVM and MLP Neural Network's supervised regression ML techniques. The ideal hyperparameters must be specified or adjusted during training to provide the best regression result on the test data set. One of the two selected regression-based approaches is support vector machine (SVM), since it works adequately when there is a reasonable margin of dissociation between classes and it is more productive in big-dimensional spaces. MLP not only processes large amounts of input data quickly and accurately after training, but can also tackle complex nonlinear problems.

A well-liked technique for supervised classification and regression is SVM. SVMs are based on the premise that data that cannot be separated linearly may be moved to a new location where they can be separated linearly using a hyper-plane that appropriately separates the data under two essential conditions. Because other sets of vectors would behave differently, we employ the hyperplane vector distances. The assumption function h is defined in Equation (3) as follows.

$$h(x_i) = \begin{Bmatrix} +1 & if \;\; w.x + b \geq 0 \\ -1 & if \;\; w.x + b < 0 \end{Bmatrix} \quad \ldots\ldots\ldots\ldots (3)$$

Locations on or above the hyperplane will be categorised as class +1, and those below the hyperplane as class -1.

Artificial neural network (ANN) known as a multi-layer perceptron neural network (MLPNN) can have several hidden layers. Figure 4.3 depicts the layer-by-layer design of the system. A single neural model neural network is called a perceptron. Given that it simulates extremely nonlinear functions, it serves as the foundation for deep learning neural networks. Equation (4) illustrates the error in a output node j at the nth data point (training example).

$$e_j(n) = d_j(n) - y_j(n) \quad \ldots\ldots\ldots\ldots(4)$$

Where,

'd' represents the goal value; 'y' represents the output value.

Equation (5) illustrates how the weights can be changed in response to modifications that reduce the total output error.

$$\in(n) = \frac{1}{2} \sum_j e_j^2(n) \quad \ldots\ldots\ldots\ldots (5)$$

Hyperparameter tuning or optimisation is the process of choosing the ideal hyperparameters for a model-learning method. Training outcomes can be modified by adjusting the value of a parameter known as a hyperparameter. Grid search, the quickest and easiest way to fine-tune hyperparameters, is employed here. For each possible combination of the provided hyper-parameter values, we construct a trained model, and then we compare their average scores to determine the best design.

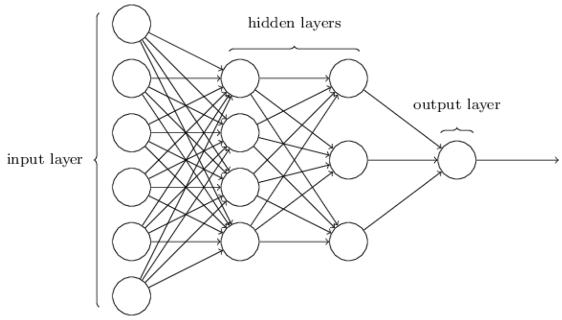

Figure 4.3 Layer wise architecture of MLPNN

Below, we detail how to adjust the model's hyper-parameters.

step1: Outline the components of a ML model.

step2: Determine the range of values that can be used for each hyperparameter in the chosen method.

step3: Determine how values of hyperparameters will be sampled.

step4: Develop some standards by which to evaluate the model.

step5: Design a cross-validation method to assess the system's performance.

4.3.4 Deploy Model

During deployment, data is put through its paces against a trained model, and the system's performance is measured across a variety of metrics. A hydroponic model at the device layer is controlled by data sent from the fog layer using the label anticipated from the previous layer's output.

4.4 Algorithm Steps of the Proposed Model

ALGORITHM

INPUT

"Features Set"

- ***Input*** – CO_2 gas level in ppm, soil moisture in percent, light intensity in lux, humidity in percent, and temperature in Celsius.
- ***Output*** - ON/OFF time duration of the pump, ventilation fan, amount of light.

OUTPUT

Predicted output with label values (regression).

Step1: Data gathering from all the input sources.

Step2: Create the label and feature data from the values of the raw data set in the datasets.

Step3: For each feature's data, apply feature engineering.

Step4: Replace the mean values with the missing and unidentified values.

Step5: Find the normalised value of the entire feature collection.

Step6: Scale every feature data to fall within a certain range.

Step7: Choose the ML model for MLP, SVM, and regression.

Step8: Select the range of possible values for the ML algorithm's hyperparameters.

Step9: Utilise the Grid Search CV Optimisation technique to improve the hyperparameter values.

Step10: Analyse and choose the ideal estimator and score for the chosen classifier.

Step11: Apply the K-Fold Validation Learning Method to the model validation.

Step12: Set the best hyperparameters that have been optimised for ML training.

Step13: Set up the training dataset's feature and label data from scratch.

Step14: Develop the model for the corresponding ML algorithms.

Step15: Using the K-fold cross-validation method, verify the model's performance.

Step16: Save/deploy the trained model if validation is successful; otherwise, go back to steps two or ten.

Step17: Create the feature data from scratch for the test data set.

Step18: The trained ML algorithm model should be loaded.

Step19: Regression analysis: forecast the outcomes given the label values.

Step20: To check the performance of the system, evaluate RMSE (Regression).

4.5 Summary of the Chapter

In this chapter, a decision-making model with data analytics is developed using ML for Precision Management with two main objectives, namely an intelligent system and a precision management system.

Two supervised machine learning (ML) algorithms, SVM and MLP, are used to build an intelligent system for actuator control based on environmental sensing input from greenhouses.

The precision management system is performed using the same two supervised regression-based algorithms, SVM and MLP regressor, for precise control of actuators.

Performance is analysed and validated for two approaches used in the system.

CHAPTER 5 EXPERIMENTAL RESULTS AND DISCUSSION

5.1 Performance Statistical Measures

A confusion matrix is used to gauge the system's effectiveness. While RMSE is computed for regression models using the confusion matrix parameters true positive (TP), false positive (FP), true negative (TN), and false negative (FN), accuracy, sensitivity (recall), specificity, and f-score are computed for classification models with positive predictive value (PPV), i.e., precision, negative predictive value (NPV), false negative rate (FNR), and false positive rate (FPR). Sensitivity, i.e. recall measures the model's capacity to correctly identify instances of the positive class, whereas specificity assesses its capacity to correctly identify instances of the negative class. In some applications, one statistic could be more important than another. The F-score, a machine learning evaluation metric, evaluates the accuracy of a model. It incorporates a model's recall and precision ratings. The accuracy statistic shows how often a model predicts accurately throughout the dataset. Most of the time, the F score is more useful than accuracy, especially if your class is divided unequally. Accuracy performs best when false-positive and false negative costs are roughly equal. If there is a large difference in the costs of false positives and false negatives, it is desirable to incorporate both precision and Recall.

1. Accuracy = (TP + TN) / (TP + TN + FP + FN)
2. Sensitivity = TP / (TP + FN)
3. Specificity = TN / (TN + FP)
4. F-score = 2 * TP / (2TP + FP + FN)
5. Positive Predictive Value (PPV) = TP / (TP + FP)
6. Negative Predictive Value (NPV) = TN / (TN + FN)
7. False Negative Rate (FNR) = FN / (FN + TP)
8. False Positive Rate (FPR) = FP / (FP + TN)
9. RMSE = sqrt (sum ((predicted_label - actual_ label)^2) / total predictions)

5.2 Experimental Setup

Two crops, gerbera daisies and broccoli, were used to put the suggested experimental strategy through its paces in real world settings. Some of the output attributes in the obtained dataset include pump on/off, ventilation fan on/off, light level (low/medium/high), CO_2 gas level (ppm), soil moisture (percent), light intensity (lux), humidity (percent) and temperature (Celsius). The values in the dataset are recorded under various conditions at various times throughout each day. For the initial part of the project, supervised ML algorithms must be used to automate actuators, build sensor nets for intelligent greenhouse monitoring, and generate basic embedded models for plant growth and feeding. On a laptop running Windows 10 (64 bit) with Intel Core i5 a 2.30GHz CPU, 8GB RAM, and no other software open, analytics and decision-making models were categorised. The MATLAB Statistics and ML Toolbox (SMT) and MATLAB Integrated Development Environment (IDE) were used to write the model code.

The recommended approach uses an embedded system to conduct a reliable analysis of CO_2, soil moisture, temperature, and plant light in greenhouse operations. As the measurements are taken under various environmental conditions, they are all monitored in real time on a personal computer through serial transmission. As data is published from nodes to Adafruit's broker, it can be seen in the Adafruit IO Cloud dashboard for remote monitoring of all these sensors. The user may then subscribe to this information to get updates as they occur.

5.3 Data Classification Using ML Model

The intelligent Model, Statistics, and ML Toolbox was built with the help of the MATLAB IDE (Integrated Development Environment). RMSE was studied, a metric used to assess system performance. Table 5.1 shows the final range chosen for both classifiers and the hyperparameters needed to improve regression modelling for each classifier.

Table 5.1 Optimization of Regression Model Hyperparameters.

Prediction Algorithm (Regression)	**Model Parameter**	**Range Searched**	**Range Selected**
SVM Regressor	kernel	rbf, poly, sigmoid	poly
	max_iter	10, 30, 50	10
MLP Regressor	Hidden_layer_size	10, 50, 100	100
	max_iter	100, 200, 300	200

The hyperparameter-tuning stage of the evaluation procedure is shown in both Table 5.2 and Figure 5.1. The importance of "Hyperparameter Tuning (HPs-T)" for choosing the best deep learning or machine learning model and enhancing the model(s)' performance. Make it simple because selecting a machine learning model is a challenging task that depends only on selecting the right set of hyperparameters. These are everything that is required to train a model. With a more tolerable variety of hyperparameter tuning and selection strategies, the performance of the machine learning model ultimately improves. It always refers to the model's parameters, and it is crucial to remember that they cannot be determined from the data and must be given before the model moves on to the training phase. Hyperparameter tweaking for the regression technique for SVM and MLP is done in the suggested model.

Table 5.2 Training and testing evaluation time (hyperparameter tuning).

Phase	**Regression**	
	SVMR	**MLPR**
Training	315.78	446.27
Testing	72.95	75.21

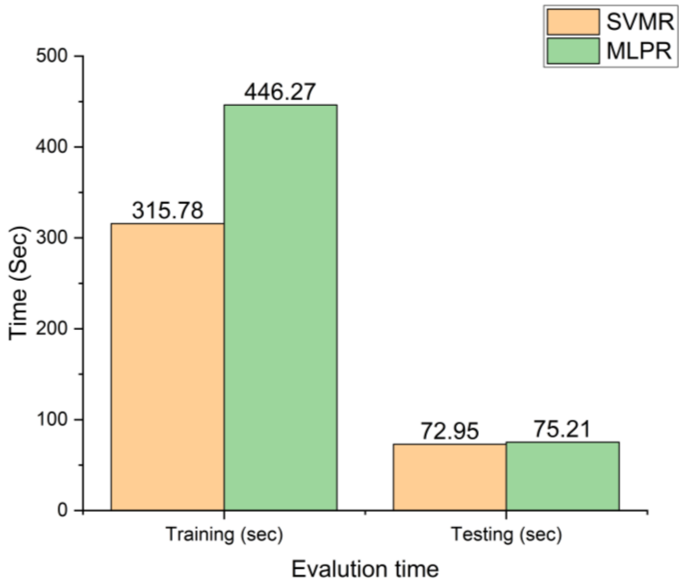

Figure 5.1 Representation of evaluation time.

After applying the suggested algorithms to the benchmark dataset, the decision making model evaluates the confusion matrix for regression and classification models to determine whether or not the desired result was achieved and to compute the various metrics, such as accuracy, sensitivity, latency, etc. MATLAB, along with a statistics and ML toolbox, was used to train and evaluate the model using the SVM and MLP-ANN supervised ML models. Both methods need optimal hyperparameters for model training, which were derived by employing the grid search CV technique.

The actual data and forecast data for the observation of the RMSE value for pump, fan, and light using the support vector machine (SVM) method are depicted in Figures 5.2-5.4.

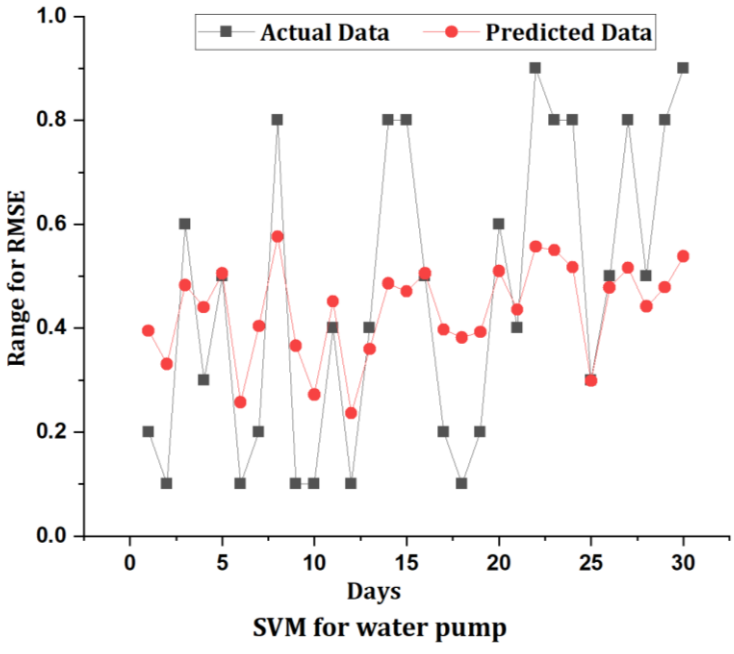

Figure 5.2   Representation of actual and prediction data for pump SVM.

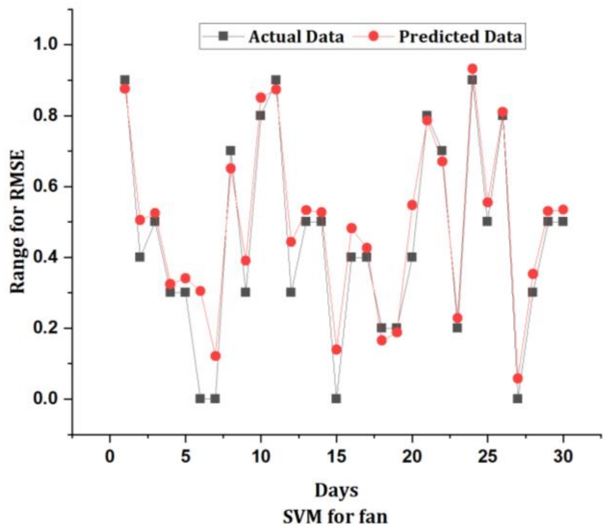

Figure 5.3   Representation of actual and prediction data for fan SVM.

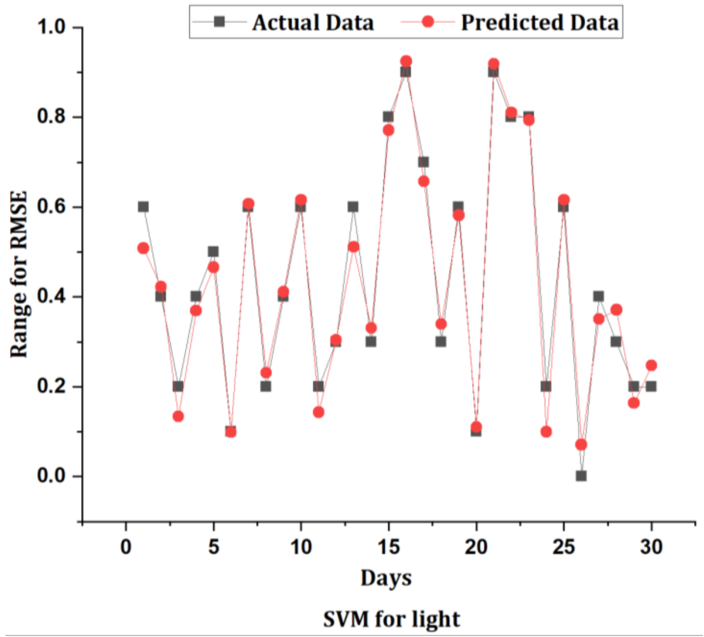

Figure 5.4 Representation of actual and prediction data for light SVM.

The Root Mean Squared Error (RMSE) is one of the two main performance indicators for a regression model. It determines the usual discrepancy between the predicted values and the actual values. It provides a gauge of the model's precision, or how effectively the desired quantity can be predicted. The Root Mean Squared Error decreases with model quality. In a perfect model, which is a hypothetical model that would always predict the precise expected result, the Root Mean Squared Error would be 0. The Root Mean Squared Error has the advantage of being easy to comprehend because the error amount is stated in the same unit as the predicted column.

Multilayer perceptron (MLP) algorithm is used to represent the actual data and forecast data for the pump, fan and light in Figures 5.5–5.7. The difference between the actual data and predicted data is not that great in SVM as compared to MLP. SVM have a shorter range of RMSE values, which clearly states that it has a lower error and more precision as far as the proposed model is concerned.

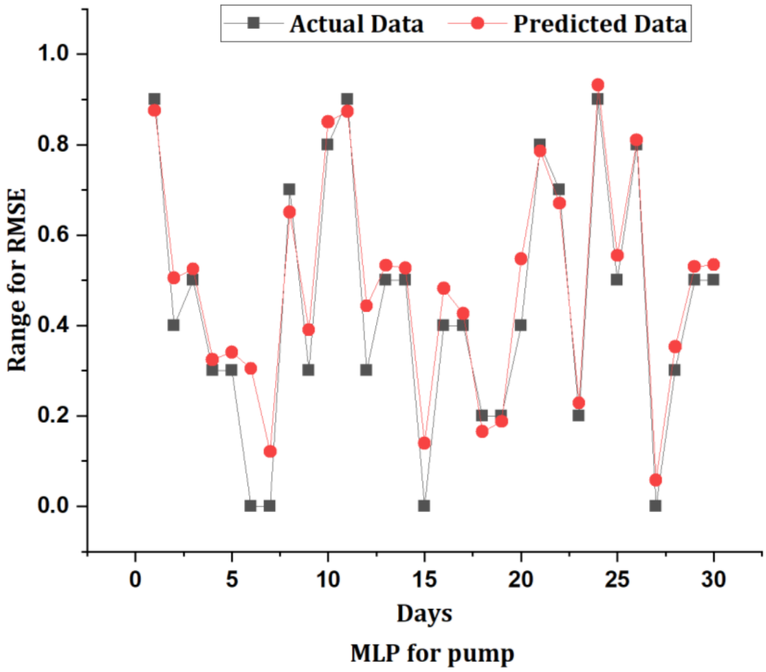

Figure 5.5 Representation of actual and prediction data for pump MLP.

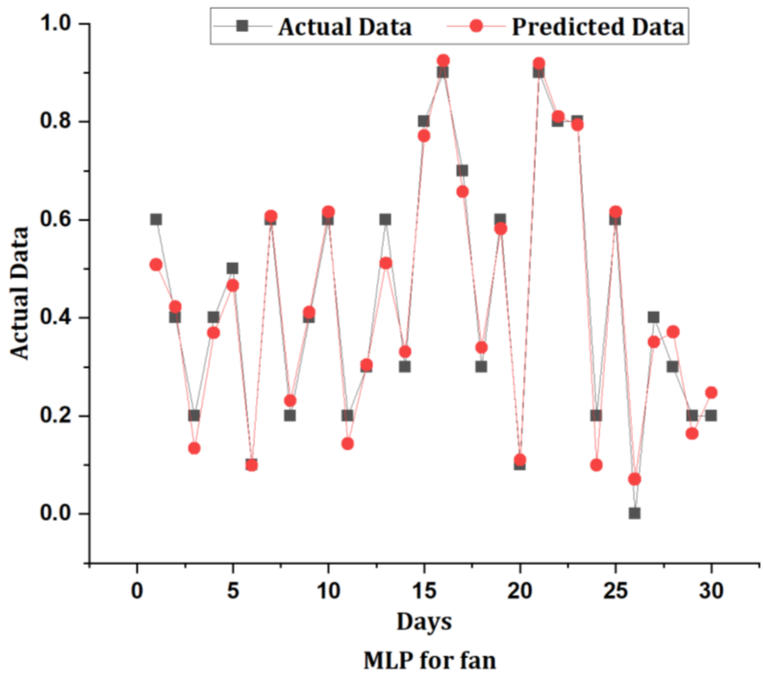

Figure 5.6 Representation of actual and prediction data for fan MLP.

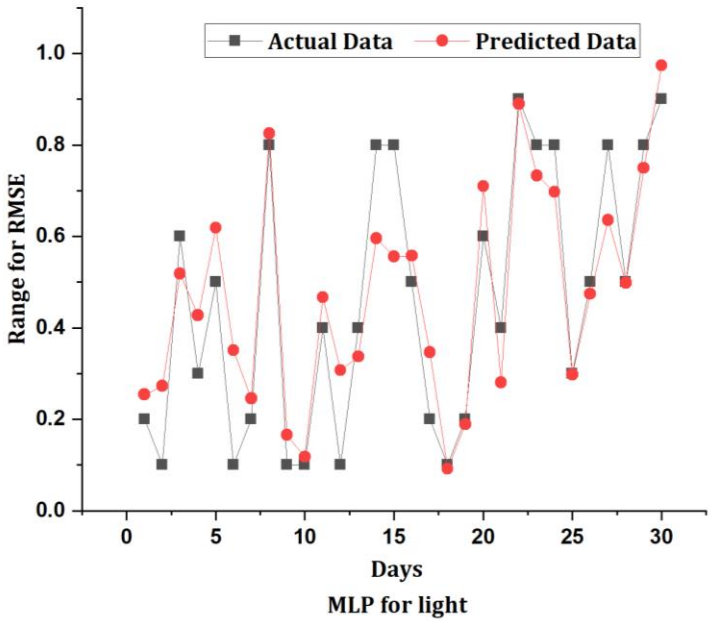

Figure 5.7 Representation of actual and prediction data for light MLP.

A typical rule of thumb states that the model can reasonably predict the data dependably when the RMSE value is between 0.2 and 0.5. A score of adjusted R-squared greater than 0.75 is also highly recommended for accuracy demonstration. An adjusted R-squared of 0.4 or higher is also acceptable in some situations. The fact that no number in any of the RMSE graphs shown above exceeds one indicates that the system is working correctly and with more accuracy.

The simulation results for the SVM and MLP algorithms used for classification modelling are shown in Figure 5.8 to figure 5.13. Figure 5.8 shows the confusion matrix for the pump MLP algorithm.

Figures 5.8 and 5.11, which are referenced below, depict the simulation results for the SVM and MLP algorithms used for classification modelling. The results of the classification report and confusion matrix for pump, fan and light as output qualities are shown below. Figure 5.8 shows that out of 30 samples the 22 samples were true positive, 1 sample is false positive, 0 samples are false negative and 7 samples are true negative, leading to 96.7% Accuracy, 3.3% error rate, 100% sensitivity, 87.5% specificity, and 96.49% F-score.

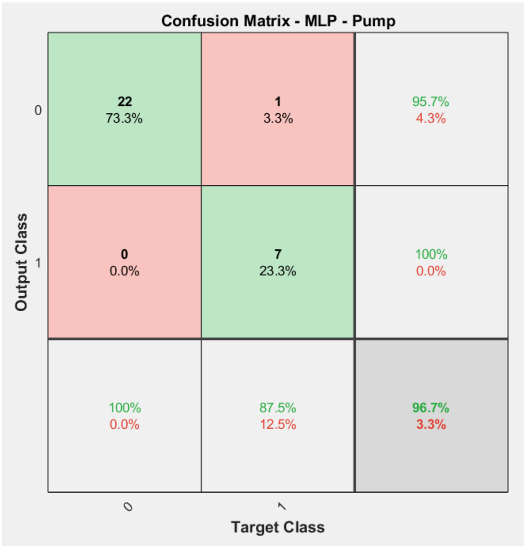

Figure 5.8 Confusion matrix using MLP for pump.

Figure 5.9 shows that of the 30 samples the 16 samples were true positive, 0 sample is false positive, 1 sample is false negative, and 13 samples are true negative which leads to 96.7% accuracy, 3.3% error rate, 94.1% sensitivity, 100% specificity, and 98.76% F-score.

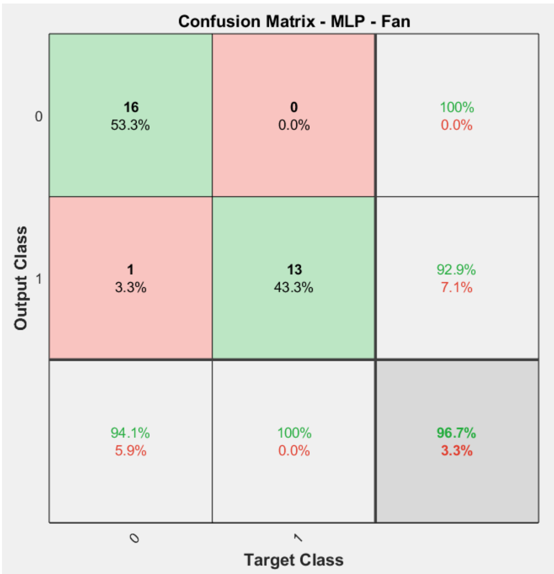

Figure 5.9 Confusion matrix using MLP for fan.

Figure 5.10 shows that out of 30 samples the 19 samples were true positive, 0 sample is false positive, 0 sample is false negative, and 11 samples are true negative which leads to 100% accuracy, 0% error rate, 100% sensitivity, 100% specificity, and 100% F-score.

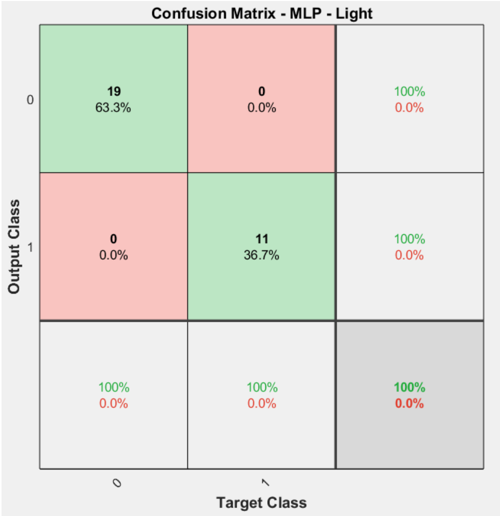

Figure 5.10 Confusion matrix using MLP for light.

For confusion matrix using SVM showing in figure 5.11 for pump proposed system got 18 true positive values, 8 true negative values, 0 false positive values, and 4 false negative values which leads to 86.7% accuracy, 13.3% error rate, 81.8% sensitivity, 100% specificity, and 95.74% F-score.

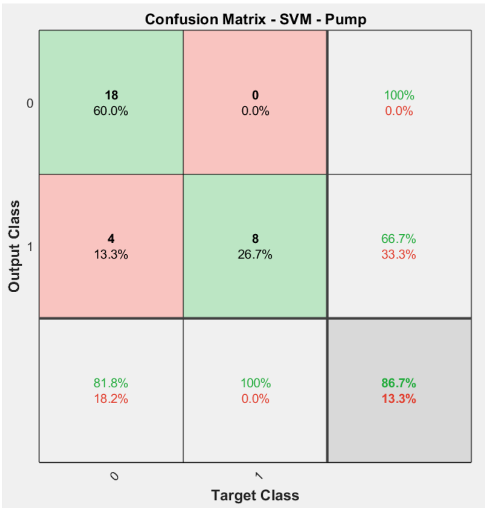

Figure 5.11 Confusion matrix using SVM for pump.

For confusion matrix using SVM shown in figure 5.12 for fan proposed system got 16 true positive values, 11 true negative values, 2 false positive values, and 1 false negative values which leads to 90% accuracy, 10% error rate, 94.1% sensitivity, 84.6% specificity and 89.88% F-score.

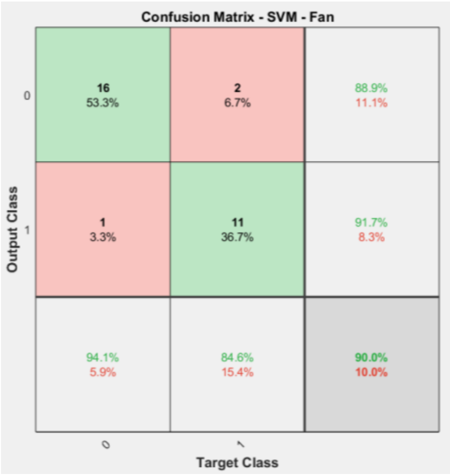

Figure 5.12 Confusion matrix using SVM for fan.

For confusion matrix using SVM shown in figure 5.13 for light proposed system got 19 true positive values, 10 true negative values, 1 false positive values and 0 false negative values which leads to 96.7% accuracy, 3.3% error rate, 100% sensitivity, 90.9% specificity and 95.95% F score.

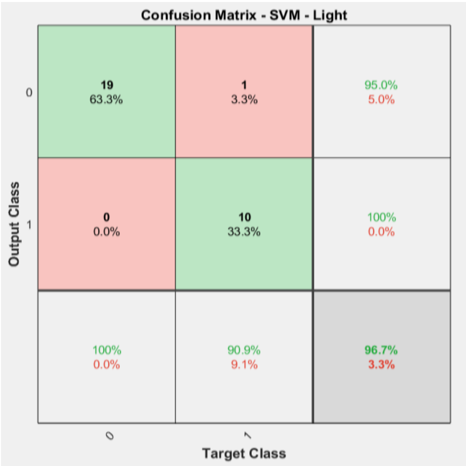

Figure 5.13 Confusion matrix using SVM for light.

Table 5.3 depicts the evaluation time required for training and testing of classification model for both algorithms SVM and MLP for three attributes actuator control pump, fan, and light for on/off operation. It is observed that based on the attributes data, train and test time varies for respective algorithms from figure 5.14 and figure 5.15.

Table 5.3 Evaluation time required of classification model

Attributes	**Training Time (sec)**		**Testing Time (sec)**	
	SVM	**MLP**	**SVM**	**MLP**
Pump	4.56	4.89	3.81	3.93
Light	4.25	4.40	3.75	4..02
Fan	4.82	4.96	4.10	4.21

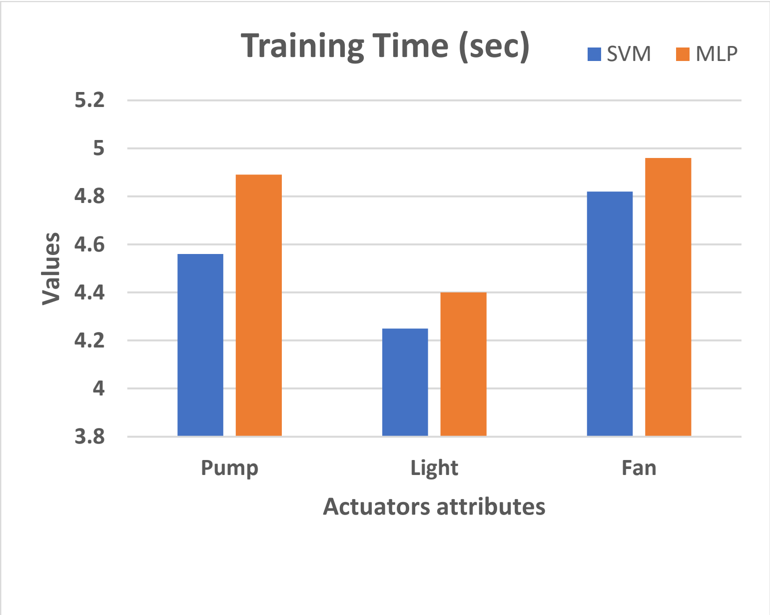

Figure 5.14 Evaluation time required for training for classification model.

The evaluation time required for the MLP algorithm is more as compared to the SVM algorithm for training data set, which differentiate latency in the proposed system. The evaluation time required for the MLP algorithm is more as compare to the SVM algorithm for testing dataset due to a greater number of hyperparameters of MLP which differentiate latency in the proposed system.

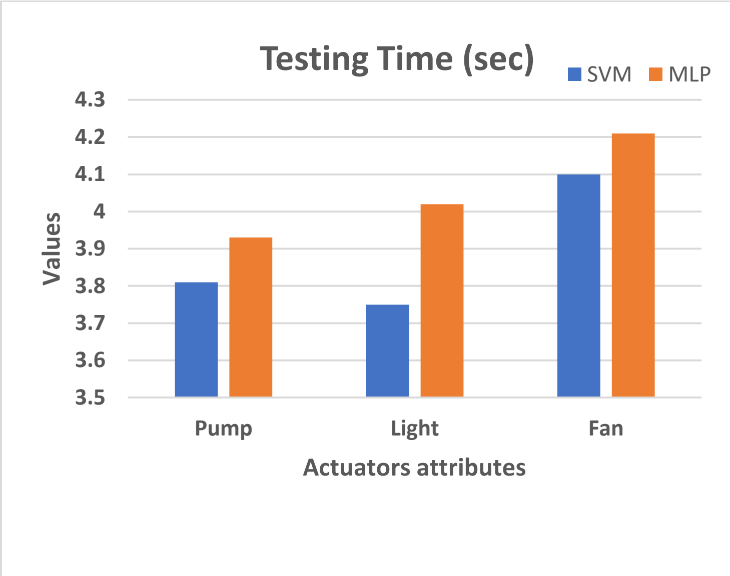

Figure 5.15 Evaluation time required for testing for classification model.

Table 5.4 displays the results of the confusion matrix-based classification model for actuator control operation to on/off for three devices. Based on the data shown in the table below, it can be concluded that the MLP method outperforms the SVM in every measure considered to control the actuators pump, light and fan as on/off perfectly.

Table 5.4 Performance evaluation of classification model

Attributes	Accuracy (%)		Sensitivity (%)		Specificity (%)		F-score (%)	
	SVM	MLP	SVM	MLP	SVM	MLP	SVM	MLP
Pump	86.66	96.66	81.81	100	100	87.5	95.74	96.49
Light	96.66	100	100	100	90.90	100	95.95	100
Fan	90	96.66	94.11	94.11	84.61	100	89.88	98.76

Similarly, the other performance evaluation parameters are evaluated from confusion matrix attributes, PPV, NPV, FNR, and FPR as shown in Table 5.5. It has been found that the suggested system can effectively classify the with greater PPV and NPV values as well as with minimal FNR and FPR ratio values.

Table 5.5 Performance Evaluation of Regression Model

Attributes	PPV (%)		NPV (%)		FNR (%)		FPR (%)	
	SVM	MLP	SVM	MLP	SVM	MLP	SVM	MLP
Pump	100	95.65	66.66	100	18.18	0	0	12.5
Light	95	100	100	100	0	0	9.09	0
Fan	88.88	100	91.66	92.85	5.88	5.88	15.38	0

The receiver operating characteristics (ROC) for classification modelling using two algorithms SVM and MLP, for pump, fan, and light actuator attributes. Figure 5.16 shows that proposed system has higher true positive rate than a minimal false positive rate. A graph showing how well a classification model performs at every level of categorisation is called the receiver operating characteristic curve (ROC curve). On this curve, two parameters are plotted: FPR and TPR.

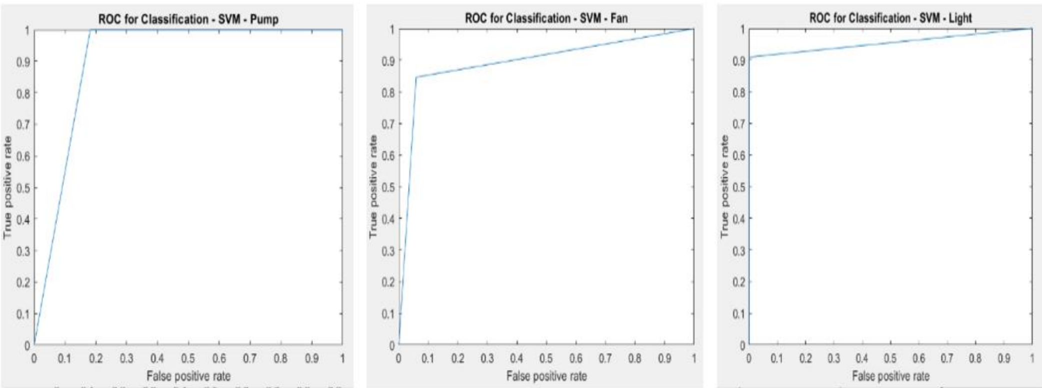

Figure 5.16 ROC for classification using SVM (Pump, Fan, Light)

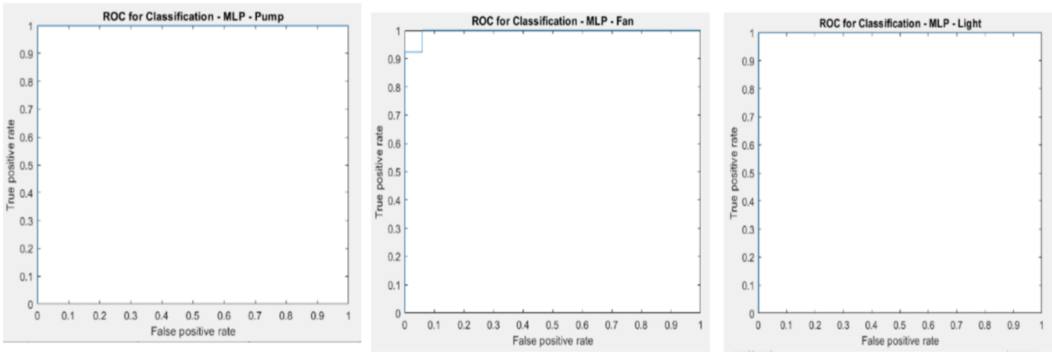

Figure 5.17 ROC for classification using MLP (Pump, Fan, Light)

Figure 5.17 shows the graph for ROC for classification using MLP for three parameters, i.e., pump, fan and light.

Figures 5.18 and 5.19 exhibit the SVM and MLP algorithms for regression modelling. Here, we can see the results of a regression analysis conducted on the output attributes of pump, fan, and light. Table 5.7 displays the evaluation of the regression model's efficacy. The table and its visual depiction in Figure 5.20 reveal that the SVM regressor method outperforms the MLP regressor for all three output qualities.

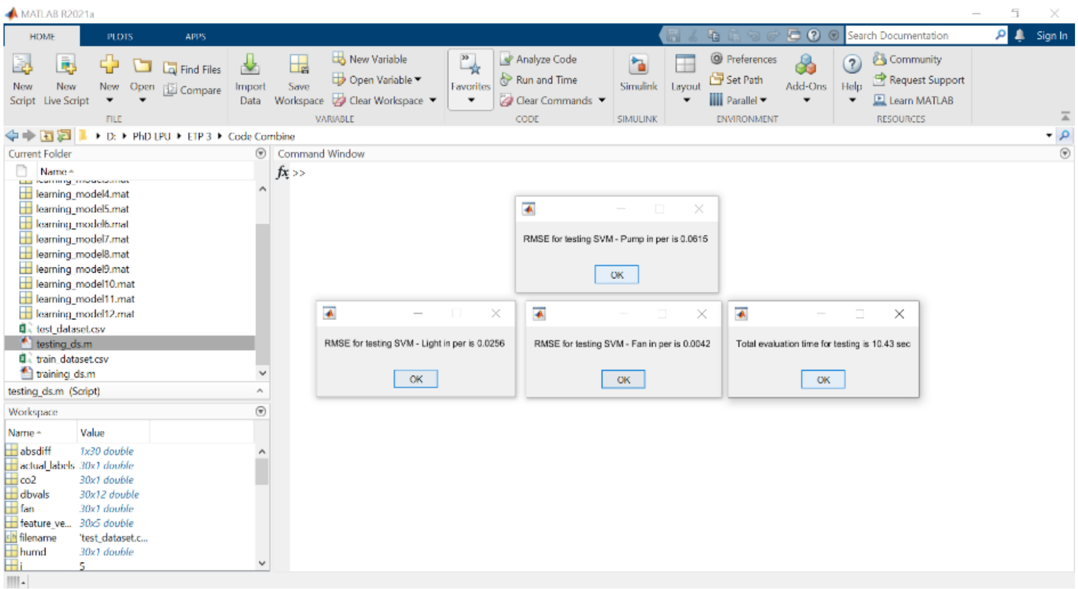

Figure 5.18 Results of the Regression Approach for RMSE SVM

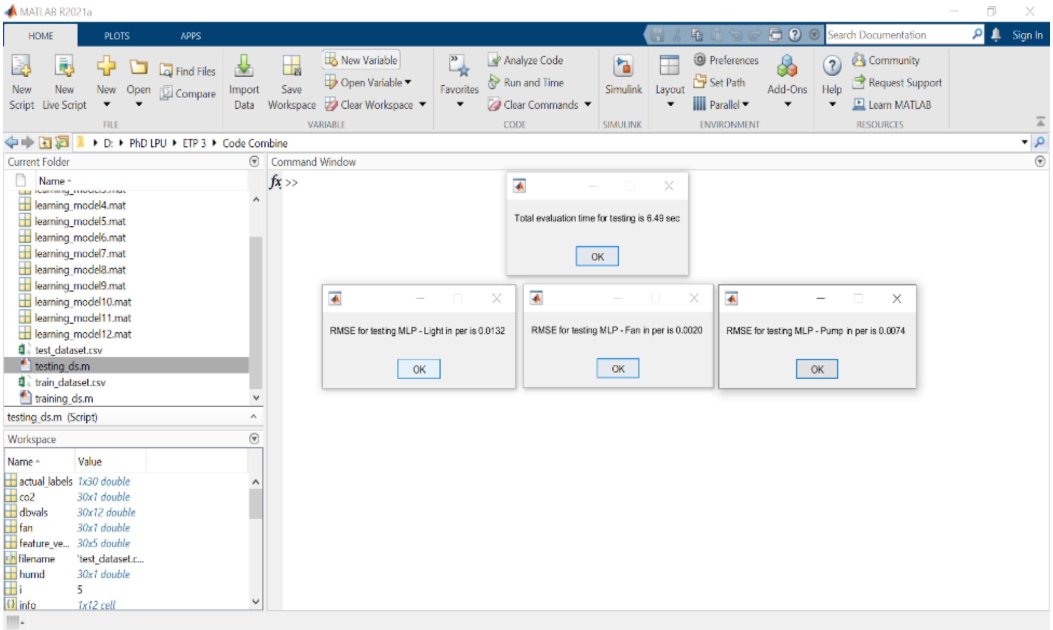

Figure 5.19 Results of the Regression Approach for RMSE MLP

Table 5.6 Evaluation time required of regression model

Attributes	**Training Time (sec)**		**Testing Time (sec)**	
	SVM	**MLP**	**SVM**	**MLP**
Pump	5.01	5.89	4.10	4.28
Light	5.45	5.63	4.35	4..79
Fan	5.30	5.42	4.58	5.05

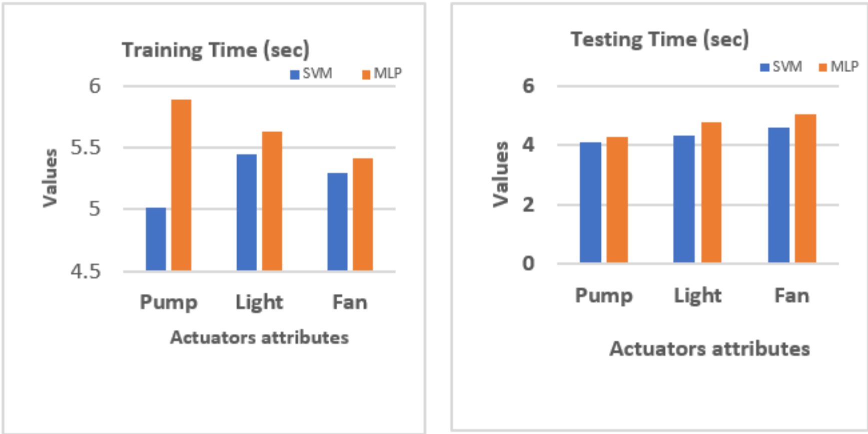

Figure 5.20 Training & Testing time for regression model

The evaluation time required for training and testing of data is calculated in seconds. In both the cases of training and testing, it is observed MLP taking more time as compared to SVM. Here, one can say that SVM outperform MLP in case of evaluation time in proposed methodology.

Table 5.7 Performance evaluation of regression model

Attributes	**RMSE**	
	SVM	**MLP**
Pump	0.0615	0.0074
Fan	0.0042	0.0020
Light	0.0256	0.0132

Finally, a comparison to the current state of the art approaches is shown in Table 5.8. The results show that the proposed classification and regression model for intelligent and precise smart farming in greenhouses produces better results when accuracy, sensitivity, and specificity of the classification model are compared with the root-mean-square-error (RMSE) of the regression model.

Table 5.8 The Result of Comparative Analysis

Ref	Accuracy (%)	Sensitivity (%)	Specificity (%)	F-Score (%)	Latency (sec)	RMSE
[74]	96.31	93.59	94.63	96.30	NI	NI
[75]	NI	NI	NI	NI	NI	0.2431
[76]	84	NI	NI	NI	NI	NI
[78]	97.31	97.31	99.00	97.30	NI	NI
[84]	85	NI	NI	NI	NI	0.02726
Proposed Work	**97.77**	**98**	**98.83**	**98.41**	**6.49**	**0.0615**

NI- Not Investigated in research.

The comparative analysis from contemporary methods with the proposed method is explain in Table 5.8 in which authors of Ref [74] proposed IOT based smart farming system along with an efficient prediction method called WPART based on supervised machine learning techniques are used in which the filter and wrapper feature selection approach is used to analyse the environmental indicators. Similarly Ref [75] uses support vector machine (SVM) and logistic regression (LR) model with MQTT. Using decision tree algorithm Ref [76] achieves 84% accuracy in proposed model. Ref [78] uses Vgg16 plus SVM for leaf disease identification and Ref [84] achieves 85% accuracy by using CNN and SVM based model.

The results show that the proposed system is worked with high precision by implementing the proper resource utilisation and comparing the system parameters like accuracy, sensitivity, specificity, F-Score, latency, and RMSE. The results extracted from the proposed work are the average values of the MLP classification and SVM regression algorithm for better results.

Table 5.9 shows the results of a comparison of several models that have been developed so far. Figure 5.21 shows a comparison between the suggested model and the standard methods currently used to develop intelligent agricultural systems.

Table 5.9 Comparative analysis of various existing studies.

Ref.	Technique(s)/Models Used	Feature	System Accuracy
[11]	Rasbery Pi & Open Cv	Focus on automating pH control.	92%
[74]	WPART and ML	Decision Support for Prediction.	96.31%
[78]	Vgg 16 Plus SVM	Controls Temperature and Humidity	97.31%
[84]	CNN & SVM	Provided Smart sensing system and opportunities	85%
Proposed Work	SVM and MLP	Low-cost real time monitoring and control control	97.77%

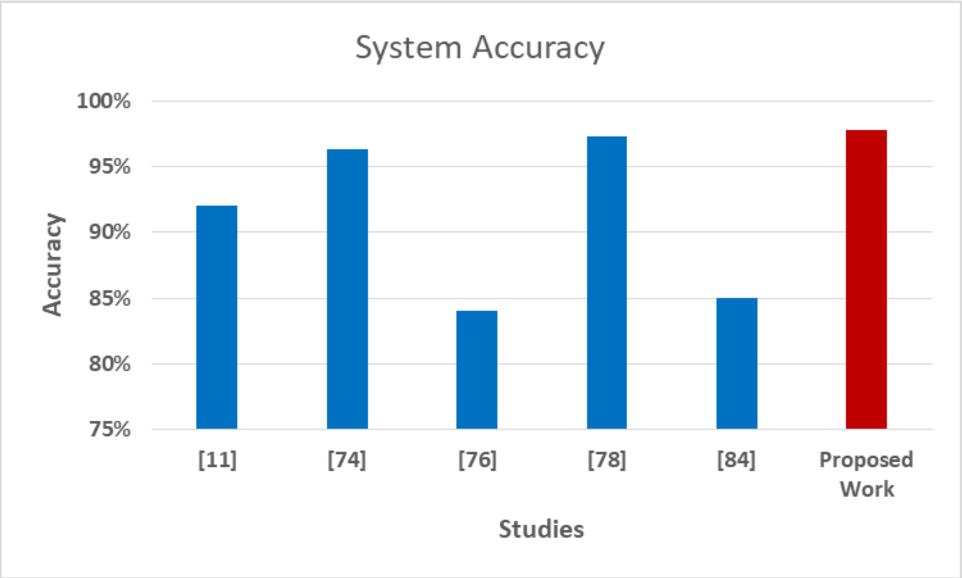

Figure 5.21 Representation of accuracy value in %.

Table 5.10 further shows that our proposed model is significantly better than those presented by other authors based on the research sensor and technology used to create the system.

Table 5.10 Comparative analysis table.

Parameters		References				
		Subahi et al. 2020 [3]	A. Carrasquilla-Batista et al. 2019 [9]	Codeluppi et al. 2019 [14]	A. Araby et al. 2019 [75]	Proposed Model
Sensors Used	Temperature	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
	Humidity	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
	Soil Moisture	No	No	**Yes**	**Yes**	**Yes**
	Light Intensity	No	No	No	No	Yes
	CO2	**Yes**	No	No	No	Yes
Technology Used	IoT	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
	ML	No	No	No	**Yes**	**Yes**
	Precision Agriculture	No	**Yes**	No	No	Yes

From the above research table, it is found that researchers have taken the initiative towards precision agriculture but the proposed model considered almost everything i.e. crop sensors and technology to make an effective smart greenhouse management system using machine learning enabled Internet of Things. This proposed system can be easily used and handled by farmers for their crop wellness.

5.4 Summary of the Chapter

In this chapter, considering the prototype model environment, proposed system is developed, simulated, and analysed based on various conditions in smart greenhouse farming environment.

The two main predictive model-based classification and regression algorithms are interpreted for the best accuracy with the MLP algorithm.

Also, the performance of proposed model is analysed with current work, and it is found that proposed model is much more capable in case of accuracy, sensitivity, specificity, latency, RMSE, and F-score.

We can conclude that the developed precision controlled greenhouse management system is compared and analyzed with the help of different parameters like training and testing evaluation time, actual and predicted data and total evaluation time required for SVM and MLP alrorithms.

When compared and analysed with the existing system, the overall accuracy of the system is 92% with low-cost implementation.

It is also observed that in some MLP algorithm the proposed system has reached upto 100 % accuracy, 100% sensitivity, 100% specificity and 100% f-score with zero error rate.

CHAPTER 6 CONCLUSION AND FUTURE SCOPE

6.1 Conclusions

The study proposes a method through which an intelligent greenhouse automation is upgraded by using IoT technologies and concepts. A user can now control and monitor data transfer between a device and a fog layer, and vice versa, using real-time sensor data. In order to improve agricultural output, the IoT concept is applied to the system by centralising data storage and processing in a reliable cloud. Precision in the data rectifies the proper utilisation of resources. The use of the IoT reduces maintenance expenses.

The proposed system will correctly monitor and adjust greenhouse characteristics such soil moisture, carbon dioxide levels, temperature, humidity, and light to assist farmers in boosting production. The model is validated by using data from actual greenhouses to determine the optimum soil moisture, carbon dioxide, temperature, humidity, and light for producing broccoli and gerbera. The proposed monitoring system will be used for any crop that can be cultivated inside the greenhouse. This results in disease free and large production of the crop.

The unique greenhouse system is developed for precise control using supervised ML techniques based on classification and regression. The proposed approach is applicable in a smart agricultural context where an IoT-based decision-making paradigm is used. Classification and regression models are the two types of analytics used to create programmes for smart and accurate farming. Both SVM and MLP can be used for these modelling purposes.

Finally, the performance of the smart farming system in intelligent and precise farming is assessed using classification and regression-based supervised ML algorithms. The results demonstrated that MLP outperformed SVM and other cutting-edge classification algorithms. The MLP system accuracy is 97.77%, sensitivity is 98%, specificity is 98.83%, and F-score is 98.41% with a lower error rate achieved by the system. The suggested technique also provided the most accurate predictions for actuators and the most precise control.

6.2 Future Scope

- Expanding the sensor parameters to include pH, CE, and other soil micro-nutrient measurement sensors to obtain more accurate data and lend a hand to the AI system in its prediction efforts can be done.
- In addition, by strengthening and weatherproofing the proposed model and applying solar panel to the greenhouse, the cost of execution would be reduced in practical settings.
- By using deep learning models trained on massive dataset samples, model performance can be improved for security parameters.

BIBLIOGRAPHY

[1] Zamora-Izquierdo, Miguel & Santa, José & Martinez, Juan & Martínez, Vicente & Skarmeta, Antonio. (2019). Smart farming IoT platform based on edge and cloud computing. Biosystems Engineering. 2019. 4-17. 10.1016/j.biosystemseng.2018.10.014.

[2] Chehri, Abdellah & Chaibi, Hasna & Rachid, Saadane & Hakem, Nadir & Wahbi, Mohamed. (2020). ScienceDirect “A Framework of Optimizing the Deployment of IoT for Precision Agriculture” Industry-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0/) Peer-review under responsibility of KES International.

[3] Subahi, Ahmed & Bouazza, Kheir Eddine. (2020). An Intelligent IoT-Based System Design for Controlling and Monitoring Greenhouse Temperature. IEEE Access. PP. 1-1. 10.1109/ACCESS.2020.3007955.

[4] Kour, Vippon & Arora, Sakshi. (2020). Recent Developments of the Internet of Things in Agriculture: A Survey. IEEE Access. 8. 129924-129957. 10.1109/ACCESS.2020.3009298.

[5] Chukkapalli, Sai & Mittal, Sudip & Gupta, Maanak & Abdelsalam, Mahmoud & Joshi, Anupam & Sandhu, Ravi & Joshi, Karuna. (2020). Ontologies and Artificial Intelligence Systems for the Cooperative Smart Farming Ecosystem. IEEE Access.

[6] B. M. M. El-Basioni and S. M. A. El-Kader, "Laying the Foundations for an IoT Reference Architecture for Agricultural Application Domain," in IEEE Access, vol. 8, pp. 190194-190230, 2020, doi: 10.1109/ACCESS.2020.3031634.

[7] R. S. Alonso, I. Sittón-Candanedo, R. Casado-Vara, J. Prieto and J. M. Corchado, "Deep Reinforcement Learning for the management of Software-Defined Networks in Smart Farming," 2020 International Conference on Omni-layer Intelligent Systems (COINS), Barcelona, Spain, 2020, pp. 1-6, doi: 10.1109/COINS49042.2020.9191634.

[8] Bandur, Doko & Jaksic, Branimir & Bandur, Milos & Jovic, Srdjan. (2019). “An analysis of energy efficiency in Wireless Sensor Networks (WSNs) applied in smart agriculture.” Computers and Electronics in Agriculture. 156. 500-507. 10.1016/j.compag.2018.12.016.

[9] A. Carrasquilla-Batista and A. Chacon-Rodriguez, "Standalone Fuzzy Logic Controller Applied to Greenhouse Horticulture Using Internet of Things," 2019 7th International Engineering, Sciences and Technology Conference (IESTEC), Panama, Panama, 2019, pp. 574-579, doi: 10.1109/IESTEC46403.2019.00108.

[10] E. -K. Tan, Y. -W. Chong, M. Niswar, B. Y. Ooi and A. Basuki, "An IoT Platform for Urban Farming," 2020 International Seminar on Intelligent Technology and Its Applications (ISITIA), Surabaya, Indonesia, 2020, pp. 51-55, doi: 10.1109/ISITIA49792.2020.9163781.

[11] Shanmukhappa Angadi, Raghavendra Katagall, "Agrivigilance: A Security System For Intrusion Detection In Agriculture Using Raspberry Pi And Opencv", INTERNATIONAL JOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH VOLUME 8, ISSUE 11, NOVEMBER 2019.

[12] S. Katamreddy, J. Walsh, S. Ward and D. Riordan, "Closed loop process control for precision farming: An Agriculture 4.0 perspective," 2019 30th Irish Signals and Systems Conference (ISSC), Maynooth, Ireland, 2019, pp. 1-6, doi: 10.1109/ISSC.2019.8904938.

[13] N. N. Misra, Y. Dixit, A. Al-Mallahi, M. S. Bhullar, R. Upadhyay and A. Martynenko, "IoT, big data and artificial intelligence in agriculture and food industry," in IEEE Internet of Things Journal, doi: 10.1109/JIOT.2020.2998584.

[14] Codeluppi, Gaia & Cilfone, Antonio & Davoli, Luca & Ferrari, Gianluigi. (2019). VegIoT Garden: a modular IoT Management Platform for Urban Vegetable Gardens. 10.1109/MetroAgriFor.2019.8909228.

[15] J. Ruan et al., "Agriculture IoT: Emerging Trends, Cooperation Networks, and Outlook," in IEEE Wireless Communications, vol. 26, no. 6, pp. 56-63, December 2019, doi: 10.1109/MWC.001.1900096.

[16] Saiz-Rubio, Veronica & Rovira-Más, Francisco. (2020). From Smart Farming towards Agriculture 5.0: A Review on Crop Data Management. Agronomy. 10. 10.3390/agronomy10020207.

[17] N. Ahmed, D. De and I. Hussain, "Internet of Things (IoT) for Smart Precision Agriculture and Farming in Rural Areas," in IEEE Internet of Things Journal, vol. 5, no. 6, pp. 4890-4899, Dec. 2018, doi: 10.1109/JIOT.2018.2879579.

[18] A. A. Araby et al., "Smart IoT Monitoring System for Agriculture with Predictive Analysis," 2019 8th International Conference on Modern Circuits and Systems Technologies (MOCAST), Thessaloniki, Greece, 2019, pp. 1-4, doi: 10.1109/MOCAST.2019.8741794.

[19] M. P. Arakeri, B. P. Vijaya Kumar, S. Barsaiya and H. V. Sairam, "Computer vision based robotic weed control system for precision agriculture," 2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Udupi, 2017, pp. 1201-1205, doi: 10.1109/ICACCI.2017.8126005.

[20] G. Archbold Taylor et al., "pH Measurement IoT System for Precision Agriculture Applications," in IEEE Latin America Transactions, vol. 17, no. 05, pp. 823-832, May 2019, doi: 10.1109/TLA.2019.8891951.

[21] M. Baghrous, A. Ezzouhairi and N. Benamar, "Towards Autonomous Farms Based on Fog Computing," 2019 2nd IEEE Middle East and North Africa COMMunications Conference (MENACOMM), Manama, Bahrain, 2019, pp. 1-4, doi: 10.1109/MENACOMM46666.2019.8988547.

[22] F. C. L. Belista, M. P. C. Go, L. L. Luceñara, C. J. G. Policarpio, X. J. M. Tan and R. G. Baldovino, "A Smart Aeroponic Tailored for IoT Vertical Agriculture using Network Connected Modular Environmental Chambers," 2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology,Communication and Control, Environment and Management (HNICEM), Baguio City, Philippines, 2018, pp. 1-4, doi: 10.1109/HNICEM.2018.8666382.

[23] W. Chen, Y. Lin, F. Ng, C. Liu and Y. Lin, "RiceTalk: Rice Blast Detection Using Internet of Things and Artificial Intelligence Technologies," in IEEE Internet of Things Journal, vol. 7, no. 2, pp. 1001-1010, Feb. 2020, doi: 10.1109/JIOT.2019.2947624.

[24] W. Chen et al., "AgriTalk: IoT for Precision Soil Farming of Turmeric Cultivation," in IEEE Internet of Things Journal, vol. 6, no. 3, pp. 5209-5223, June 2019, doi: 10.1109/JIOT.2019.2899128.

[25] L. Farhan, R. Kharel, O. Kaiwartya, M. Quiroz-Castellanos, U. Raza and S. H. Teay, "LQOR: Link Quality-Oriented Route Selection on Internet of Things Networks for Green Computing," 2018 11th International Symposium on Communication Systems, Networks & Digital Signal Processing (CSNDSP), Budapest, 2018, pp. 1-6, doi: 10.1109/CSNDSP.2018.8471884.

[26] Karim, Foughali & Fathallah, Karim & Frihida, Ali. (2019). A Cloud-IOT Based Decision Support System for Potato Pest Prevention. Procedia Computer Science. 160. 616-623. 10.1016/j.procs.2019.11.038.

[27] A. A. Gnanaraj and J. G. Jayanthi, "An Application Framework for IoTs Enabled Smart Agriculture Waste Recycle Management System," 2017 World Congress on Computing and Communication Technologies (WCCCT), Tiruchirappalli, 2017, pp. 1-5, doi: 10.1109/WCCCT.2016.11.

[28] S. Gutiérrez, I. Martínez, J. Varona, M. Cardona and R. Espinosa, "Smart Mobile LoRa Agriculture System based on Internet of Things," 2019 IEEE 39th Central America and Panama Convention (CONCAPAN XXXIX), Guatemala City, Guatemala, 2019, pp. 1-6, doi: 10.1109/CONCAPANXXXIX47272.2019.8977109.

[29] C. Hirsch, E. Bartocci and R. Grosu, "Capacitive Soil Moisture Sensor Node for IoT in Agriculture and Home," 2019 IEEE 23rd International Symposium on Consumer Technologies (ISCT), Ancona, Italy, 2019, pp. 97-102, doi: 10.1109/ISCE.2019.8901012.

[30] G. Horng, M. Liu and C. Chen, "The Smart Image Recognition Mechanism for Crop Harvesting System in Intelligent Agriculture," in IEEE Sensors Journal, vol. 20, no. 5, pp. 2766-2781, 1 March1, 2020, doi: 10.1109/JSEN.2019.2954287.

[31] G. Kakamoukas et al., "A Multi-collective, IoT-enabled, Adaptive Smart Farming Architecture," 2019 IEEE International Conference on Imaging Systems and Techniques (IST), Abu Dhabi, United Arab Emirates, 2019, pp. 1-6, doi: 10.1109/IST48021.2019.9010236.

[32] C. Kamienski et al., "SWAMP: an IoT-based Smart Water Management Platform for Precision Irrigation in Agriculture," 2018 Global Internet of Things Summit (GIoTS), Bilbao, 2018, pp. 1-6, doi: 10.1109/GIOTS.2018.8534541.

[33] N. Kitpo, Y. Kugai, M. Inoue, T. Yokemura and S. Satomura, "Internet of Things for Greenhouse Monitoring System Using Deep Learning and Bot Notification Services," 2019 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 2019, pp. 1-4, doi: 10.1109/ICCE.2019.8661999.

[34] A. Mittal, S. Sarangi, S. Ramanath, P. V. Bhatt, R. Sharma and P. Srinivasu, "IoT-Based Precision Monitoring of Horticultural Crops — A Case-Study on Cabbage and Capsicum," 2018 IEEE Global Humanitarian Technology Conference (GHTC), San Jose, CA, 2018, pp. 1-7, doi: 10.1109/GHTC.2018.8601908.

[35] S. Pooja, D. V. Uday, U. B. Nagesh and S. G. Talekar, "Application of MQTT protocol for real time weather monitoring and precision farming," 2017 International Conference on Electrical, Electronics, Communication, Computer, and Optimization Techniques (ICEECCOT), Mysuru, 2017, pp. 1-6, doi: 10.1109/ICEECCOT.2017.8284616.

[36] R. Prabha, E. Sinitambirivoutin, F. Passelaigue and M. V. Ramesh, "Design and Development of an IoT Based Smart Irrigation and Fertilization System for Chilli Farming," 2018 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), Chennai, 2018, pp. 1-7, doi: 10.1109/WiSPNET.2018.8538568.

[37] S. Sadowski and P. Spachos, "Solar-Powered Smart Agricultural Monitoring System Using Internet of Things Devices," 2018 IEEE 9th Annual Information

Technology, Electronics and Mobile Communication Conference (IEMCON), Vancouver, BC, 2018, pp. 18-23, doi: 10.1109/IEMCON.2018.8614981.

[38] S. Sarangi et al., "An Affordable IoT Edge Platform for Digital Farming in Developing Regions," 2019 11th International Conference on Communication Systems & Networks (COMSNETS), Bengaluru, India, 2019, pp. 556-558, doi: 10.1109/COMSNETS.2019.8711388.

[39] Sinha, A., Shrivastava, G., & Kumar, P. (2019). Architecting user-centric internet of things for smart agriculture. Sustain. Comput. Informatics Syst., 23, 88-102.

[40] P. Sureephong, P. Wiangnak and S. Wicha, "The comparison of soil sensors for integrated creation of IOT-based Wetting front detector (WFD) with an efficient irrigation system to support precision farming," 2017 International Conference on Digital Arts, Media and Technology (ICDAMT), Chiang Mai, 2017, pp. 132-135, doi: 10.1109/ICDAMT.2017.7904949.

[41] Khalaf, O.I., Ogudo, K.A. and Singh, M., 2021. A fuzzy-based optimization technique for the energy and spectrum efficiencies trade-off in cognitive radio-enabled 5G network. Symmetry, 13(1), p.47.

[42] Walia, G. S., Singh, P., Singh, M., Abouhawwash, M., Park, H. J. et al. (2022). Three-Dimensional Optimum Node Localization in Dynamic Wireless Sensor Networks. CMC-Computers, Materials & Continua, 70(1), 305–321.

[43] Singh, M., Kumar, M. and Malhotra, J., 2018. Energy efficient cognitive body area network (CBAN) using lookup table and energy harvesting. Journal of Intelligent & Fuzzy Systems, 35(2), pp.1253-1265.

[44] M. Hassan, M. Singh and K. Hamid, "Survey on NOMA and Spectrum Sharing Techniques in 5G," 2021 IEEE International Conference on Smart Information Systems and Technologies (SIST), 2021, pp. 1-4, doi: 10.1109/SIST50301.2021.9465962.

[45] Rokade and M. Singh, "Analysis of Precise Green House Management System using Machine Learning based Internet of Things (IoT) for Smart Farming," 2021 2nd International Conference on Smart Electronics and Communication (ICOSEC), 2021, pp. 21-28, doi: 10.1109/ICOSEC51865.2021.9591962.

[46] A. Kadu and M. Singh, "Comparative Analysis of e-Health Care Telemedicine System Based on Internet of Medical Things and Artificial Intelligence," 2021 2nd International Conference on Smart Electronics and Communication (ICOSEC), 2021, pp. 1768-1775, doi: 10.1109/ICOSEC51865.2021.9591941.

[47] Mohamed Hassan, Manwinder Singh & Khalid Hamid (2021) "IMPACT OF POWER AND BANDWIDTH ON THE CAPACITY RATE AND NUMBER OF USERS IN SC-NOMA", Harbin Gongye Daxue Xuebao/Journal of Harbin Institute of Technology, 53(9), pp. 118–124. Available at: http://hebgydxxb.periodicales.com/index.php/JHIT/article/view/726 (Accessed: 15 February 2022).

[48] M. Hassan, M. Singh and K. Hamid, "Survey on NOMA and Spectrum Sharing Techniques in 5G," 2021 IEEE International Conference on Smart Information Systems and Technologies (SIST), 2021, pp. 1-4, doi: 10.1109/SIST50301.2021.9465962.

[49] Hassan, M., Singh, M., & Hamid, K. (2021). Overview of Cognitive Radio Networks. Journal of Physics: Conference Series, 1831.

[50] S. K. Roy, M. Singh, K. K. Sharma, C. Bhargava and B. P. Singh, "Mathematical Modelling of Simple Passive RC Filters Using Floating Admittance Technique," 2020 IEEE International Conference for Innovation in Technology (INOCON), 2020, pp. 1-6, doi: 10.1109/INOCON50539.2020.9298230.

[51] M. A. Ferrag, L. Shu, X. Yang, A. Derhab and L. Maglaras, "Security and Privacy for Green IoT-Based Agriculture: Review, Blockchain Solutions, and Challenges," in IEEE Access, vol. 8, pp. 32031-32053, 2020, doi: 10.1109/ACCESS.2020.2973178.

[52] W. Gong, X. Zhang, Y. Wang, W. Tang, Y. Chen and D. Li, "Review of Intelligent Control Methods for Greenhouse Cluster Systems," 2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), 2019, pp. 235-239, doi: 10.1109/iThings/GreenCom/CPSCom/SmartData.2019.00059.

[53] M. Gupta, M. Abdelsalam, S. Khorsandroo and S. Mittal, "Security and Privacy in Smart Farming: Challenges and Opportunities," in IEEE Access, vol. 8, pp. 34564-34584, 2020, doi: 10.1109/ACCESS.2020.2975142.

[54] Navarro, Emerson & Costa, Nuno & Pereira, António. (2020). A Systematic Review of IoT Solutions for Smart Farming. Sensors. 20. 4231. 10.3390/s20154231.

[55] F. O'Donncha and J. Grant, "Precision Aquaculture," in IEEE Internet of Things Magazine, vol. 2, no. 4, pp. 26-30, December 2019, doi: 10.1109/IOTM.0001.1900033.

[56] Patil, Suhas & R, Sakkaravarthi. (2017). Internet of things based smart agriculture system using predictive analytics. Asian Journal of Pharmaceutical and Clinical Research. 10. 148. 10.22159/ajpcr.2017.v10s1.19601.

[57] J. Aleotti, M. Amoretti, A. Nicoli and S. Caselli, "A Smart Precision-Agriculture Platform for Linear Irrigation Systems," 2018 26th International Conference on Software, Telecommunications and Computer Networks (SoftCOM), 2018, pp. 1-6, doi: 10.23919/SOFTCOM.2018.8555841.

[58] D. Brunelli, A. Albanese, D. d'Acunto and M. Nardello, "Energy Neutral Machine Learning Based IoT Device for Pest Detection in Precision Agriculture," in IEEE Internet of Things Magazine, vol. 2, no. 4, pp. 10-13, December 2019, doi: 10.1109/IOTM.0001.1900037.

[59] S. Khriji, D. E. Houssaini, I. Kammoun, K. Besbes and O. Kanoun, "Energy-Efficient Routing Algorithm Based on Localization and Clustering Techniques for Agricultural Applications," in IEEE Aerospace and Electronic Systems Magazine, vol. 34, no. 3, pp. 56-66, March 2019, doi: 10.1109/MAES.2019.2905947.

[60] S. Monteleone, E. A. de Moraes and R. F. Maia, "Analysis of the variables that affect the intention to adopt Precision Agriculture for smart water management in Agriculture 4.0 context," 2019 Global IoT Summit (GIoTS), 2019, pp. 1-6, doi: 10.1109/GIOTS.2019.8766384.

[61] A. K. Pandey and M. Chauhan, "IOT Based Smart Polyhouse System using Data Analysis," 2019 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT), 2019, pp. 1-5, doi: 10.1109/ICICT46931.2019.8977665.

[62] S. Rajeswari, K. Suthendran and K. Rajakumar, "A smart agricultural model by integrating IoT, mobile and cloud-based big data analytics," 2017 International Conference on Intelligent Computing and Control (I2C2), 2017, pp. 1-5, doi: 10.1109/I2C2.2017.8321902.

[63] U. Shafi et al., "A Multi-Modal Approach for Crop Health Mapping Using Low Altitude Remote Sensing, Internet of Things (IoT) and Machine Learning," in IEEE Access, vol. 8, pp. 112708-112724, 2020, doi: 10.1109/ACCESS.2020.3002948.

[64] G. Stamatescu, C. Drăgana, I. Stamatescu, L. Ichim and D. Popescu, "IoT-Enabled Distributed Data Processing for Precision Agriculture," 2019 27th Mediterranean Conference on Control and Automation (MED), 2019, pp. 286-291, doi: 10.1109/MED.2019.8798504.

[65] J. Stewart, R. Stewart and S. Kennedy, "Internet of Things — Propagation modelling for precision agriculture applications," 2017 Wireless Telecommunications Symposium (WTS), 2017, pp. 1-8, doi: 10.1109/WTS.2017.7943528.

[66] H. Sun, Q. Zhu, J. Ren, D. Barclay and W. Thomson, "Combining Image Analysis and Smart Data Mining for Precision Agriculture in Livestock Farming," 2017 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), 2017, pp. 1065-1069, doi: 10.1109/iThings-GreenCom-CPSCom-SmartData.2017.162.

[67] A. Temprilho, L. Nóbrega, P. Pedreiras, P. Gonçalves and S. Silva, "M2M Communication Stack for Intelligent Farming," 2018 Global Internet of Things Summit (GIoTS), 2018, pp. 1-6, doi: 10.1109/GIOTS.2018.8534560.

[68] L. S. Yashaswini, H. U. Vani, H. N. Sinchana and N. Kumar, "Smart automated irrigation system with disease prediction," 2017 IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI), 2017, pp. 422-427, doi: 10.1109/ICPCSI.2017.8392329.

[69] Pei J, Yu Z, Li J, Jan MA, Lakshmanna K. TKAGFL: A Federated Communication Framework Under Data heterogeneity. IEEE Transactions on Network Science and Engineering. 2022 May 26.

[70] Gundluru, N., Rajput, D.S., Lakshmanna, K., Kaluri, R., Shorfuzzaman, M., Uddin, M. and Rahman Khan, M.A., 2022. Enhancement of Detection of Diabetic Retinopathy Using Harris Hawks Optimization with Deep Learning Model. Computational Intelligence and Neuroscience, 2022.

[71] Lakshmanna K, Subramani N, Alotaibi Y, Alghamdi S, Khalafand OI, Nanda AK. Improved Metaheuristic-Driven Energy-Aware Cluster-Based Routing Scheme for IoT-Assisted Wireless Sensor Networks. Sustainability. 2022 Jun 24;14(13):7712.

[72] Lakshmanna K, Kavitha R, Geetha BT, Nanda AK, Radhakrishnan A, Kohar R. Deep Learning-Based Privacy-Preserving Data Transmission Scheme for Clustered IIoT Environment. Computational Intelligence and Neuroscience. 2022 Jun 8;2022.

[73] Dr V. Suma, "Internet of Things (IoT) based Intelligent Agriculture in India: An Overview", Journal of ISMAC (2021), Vol.03/ No.01, Pages: 1-15, http://irojournals.com/iroismac/, DOI: https://doi.org/10.36548/jismac.2021.1.001

[74] Rezk, N.G., Hemdan, E.ED., Attia, AF. et al. An efficient IoT-based intelligent farming system using machine learning algorithms. Multimed Tools Appl 80, 773–797 (2021). https://doi.org/10.1007/s11042-020-09740-6.

[75] A. Araby et al., "Intelligent IoT Monitoring System for Agriculture with Predictive Analysis," 2019 8th International Conference on Modern Circuits and Systems Technologies (MOCAST), 2019, pp. 1-4, doi: 10.1109/MOCAST.2019.8741794.

[76] Tageldin, Ahmed & Adly, Dalia & Mostafa, Hassan & Mohammed, Haitham. (2020). Applying Machine Learning Technology in the Prediction of Crop Infestation with Cotton Leafworm in Greenhouse. 10.1101/2020.09.17.301168.

[77] Ahamed Ali Samsu Aliar, Justindhas Yesudhasan, Manjunathan Alagarsamy, Karthikram Anbalagan, Jeevitha Sakkarai, Kannadhasan Suriyan, "A comprehensive analysis on IoT-based intelligent farming solutions using machine learning algorithms", Bulletin of Electrical Engineering and Informatics, Vol. 11, No. 3, June 2022, pp. 1550~1557, ISSN: 2302-9285, DOI: 10.11591/eei.v11i3.3310

[78] Sethy, Prabira & Behera, Santi & Pandey, Chanki & Narayanand, Sridevi. (2020). Intelligent Paddy Field Monitoring System using Deep Learning and IoT. Concurrent Engineering Research and Applications. 10.1177/1063293X21988944.

[79] Naina Kaushik, Shashank Narad, Akshay Mohature, Pratik Sakpal, "Predictive Analysis of IoT Based Digital Agriculture System using Machine Learning", International Journal of Engineering Science and Computing, March 2019, Volume 9 Issue No.3.

[80] Siddiquee, Kazy Noor-E-Alam & Islam, Md & Singh, Ninni & Gunjan, Vinit & Yong, Wong & Huda, Mohammad & Naik, D.. (2022). Development of Algorithms for an IoT-Based Intelligent Agriculture Monitoring System. Wireless Communications and Mobile Computing. 2022. 1-16. 10.1155/2022/7372053.

[81] Nourelhouda, Ferehan & Haqiq, Abdelkrim & Wazih, Dr. Mohd. (2022). Intelligent Farming System Based on Intelligent Internet of Things and Predictive Analytics. Journal of Food Quality. 2022. 10.1155/2022/7484088.

[82] Sekaran, Kaushik & Meqdad, Maytham N. & Kumar, Pardeep & Rajan, Soundar & Kadry, Seifedine. (2020). Intelligent agriculture management system using internet of things. TELKOMNIKA (Telecommunication Computing Electronics and Control). 18. 1276-1285. 10.12928/TELKOMNIKA.v18i3.14029.

[83] Hanna Addisu Tefera*, Huang Dongjunb, Kevin Njagic, "Implementation of IoT and Machine Learning for Intelligent Farming Monitoring System", International Journal of Sciences: Basic and Applied Research (IJSBAR), ISSN 2307-4531

[84] Ha, Nam & Xu, Kai & Ren, Guanghui & Mitchell, Arnan & Ou, Jian. (2020). Machine Learning-Enabled Intelligent Sensor Systems. Advanced Intelligent Systems. 2. 2000063. 10.1002/aisy.202000063.

[85] Jin, Xue-bo & Zheng, Wei-Zhen & Kong, Jian-Lei & Wang, Xiao-Yi & Zuo, Min & Zhang, Qing-Chuan & Lin, Seng. (2021). Deep-Learning Temporal Predictor via Bidirectional Self-Attentive Encoder-Decoder Framework for IoT-Based Environmental Sensing in Intelligent Greenhouse. Agriculture. 11. 802. 10.3390/agriculture11080802.

[86] Akhter, Ravesa & Sofi, Shabir. (2021). Precision Agriculture using IoT Data Analytics and Machine Learning. Journal of King Saud University - Computer and Information Sciences. 10.1016/j.jksuci.2021.05.013.

[87] Quy, Vu K., Nguyen V. Hau, Dang V. Anh, Nguyen M. Quy, Nguyen T. Ban, Stefania Lanza, Giovanni Randazzo, and Anselme Muzirafuti. 2022. "IoT-Enabled Intelligent Agriculture: Architecture, Applications, and Challenges" Applied Sciences 12, no. 7: 3396. https://doi.org/10.3390/app12073396

[88] O. Elijah, T. A. Rahman, I. Orikumhi, C. Y. Leow and M. N. Hindia, "An Overview of Internet of Things (IoT) and Data Analytics in Agriculture: Benefits and Challenges," in IEEE Internet of Things Journal, vol. 5, no. 5, pp. 3758-3773, Oct. 2018, doi: 10.1109/JIOT.2018.2844296.

[89] Rashi Kaur, Kodali Havish, Thirumala Kaustub Dutt, Gangidi Manohar Reddy, "Agrocompanion: A Intelligent Farming Approach Based on IoT and Machine Learning", International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075 (Online), Volume-9 Issue-12, October 2020.

[90] Yinghan Liu (2021): Intelligent analysis platform of sustainable agricultural development based on the Internet of Things and machine learning, Acta

Agriculturae Scandinavica, Section B — Soil & Plant Science, DOI: 10.1080/09064710.2021.1943513.

[91] Sharma, A. Jain, P. Gupta and V. Chowdary, "Machine Learning Applications for Precision Agriculture: A Comprehensive Review," in IEEE Access, vol. 9, pp. 4843-4873, 2021, doi: 10.1109/ACCESS.2020.3048415.

[92] K. Lela Madhav, N. Sandeep, 2019, Machine Learning Approach for Agriculture IoT using SVM&ANN, INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY (IJERT) CONF CALL – 2019 (Volume 7 – Issue 11)

[93] Yemeserach Mekonnen, Srikanth Namuduri, Lamar Burton, Arif Sarwat, and Shekhar Bhansali, "Review—Machine Learning Techniques in Wireless Sensor Network Based Precision Agriculture", Journal of The Electrochemical Society, 2020 167 037522

[94] Perales Gómez, Á.L., López-de-Teruel, P.E., Ruiz, A. et al. FARMIT: continuous assessment of crop quality using machine learning and deep learning techniques for IoT-based intelligent farming. Cluster Comput 25, 2163–2178 (2022). https://doi.org/10.1007/s10586-021-03489-9

[95] Colombo-Mendoza, Luis & Paredes-Valverde, Mario & Salas Zarate, María & Valencia-García, Rafael. (2022). Internet of Things-Driven Data Mining for Intelligent Crop Production Prediction in the Peasant Farming Domain. Applied Sciences. 12. 1940. 10.3390/app12041940.

[96] Yang, B., Xu, Y. Applications of deep-learning approaches in horticultural research: a review. Hortic Res 8, 123 (2021). https://doi.org/10.1038/s41438-021-00560-9

[97] Cafuta, Davor, Ivica Dodig, Ivan Cesar, and Tin Kramberger. 2021. "Developing a Modern Greenhouse Scientific Research Facility—A Case Study Sensors 21, no. 8: 2575. https://doi.org/10.3390/s21082575

[98] Bakthavatchalam, Kalaiselvi, Balaguru Karthik, Vijayan Thiruvengadam, Sriram Muthal, Deepa Jose, Ketan Kotecha, and Vijayakumar Varadarajan. 2022. "IoT Framework for Measurement and Precision Agriculture: Predicting the Crop

Using Machine Learning Algorithms" Technologies 10, no. : 13. https://doi.org/10.3390/technologies10010013

[99] Alazab M, Lakshmanna K, Reddy T, Pham QV, Maddikunta PK. Multi-objective cluster head selection using fitness averaged rider optimization algorithm for IoT networks in smart cities. Sustainable Energy Technologies and Assessments. 2021 Feb 1;43:100973.

[100] Reddy GT, Reddy MP, Lakshmanna K, Kaluri R, Rajput DS, Srivastava G, Baker T. Analysis of dimensionality reduction techniques on big data. IEEE Access. 2020 Mar 16;8:54776-88.

[101] Lakshmanna K, Kaluri R, Gundluru N, Alzamil ZS, Rajput DS, Khan AA, Haq MA, Alhussen A. A Review on Deep Learning Techniques for IoT Data. Electronics. 2022 Jan;11(10):1604.

[102] Lakshmanna K, Shaik F, Gunjan VK, Singh N, Kumar G, Shafi RM. Perimeter Degree Technique for the Reduction of Routing Congestion during Placement in Physical Design of VLSI Circuits. Complexity. 2022 Apr 27;2022.

[103] Singh N, Gunjan VK, Chaudhary G, Kaluri R, Victor N, Lakshmanna K. IoT enabled HELMET to safeguard the health of mine workers. Computer Communications. 2022 Jun 25.

[104] Rajput DS, Basha SM, Xin Q, Gadekallu TR, Kaluri R, Lakshmanna K, Maddikunta PK. Providing diagnosis on diabetes using cloud computing environment to the people living in rural areas of India. Journal of Ambient Intelligence and Humanized Computing. 2022 May;13(5):2829-40.

[105] N. Kaewmard and S. Saiyod, “Sensor data collection and irrigation control on vegetable crop using smart phone and wireless sensor networks for smart farm,” in Proc. of the IEEE Conference on Wireless Sensors (ICWiSE), October, 2014, pp. 106-112.

[106] T. Baranwal and P. K. Pateriya, “Development of IoT based smart security and monitoring devices for agriculture,” in Proc. of the 6th International Conference on Cloud System and Big Data Engineering (Confluence), January, 2016, pp. 597-602.

[107] S. Pallavi, J. D. Mallapur, and K. Y. Bendigeri, “Remote sensing and controlling of greenhouse agriculture parameters based on IoT,” in Proc. of the International Conference on Big Data, IoT and Data Science (BID), December, 2017, pp. 44-48.

[108] M. Dholu and K. A. Ghodinde, “Internet of Things (IoT) for Precision Agriculture Application,” in Proc. of the 2nd International Conference on Trends in Electronics and Informatics, May, 2018, pp. 339-342.

[109] D. Davcev, K. Mitreski, S. Trajkovic, V. Nikolovski, and N. Koteli, “IoT agriculture system based on LoRaWAN,” in Proc. of the IEEE International Workshop on Factory Communication Systems (WFCS), June, 2018, pp. 1-4.

[110] S. Heble, A. Kumar, K. V. V. D. Prasad, S. Samirana, P. Rajalakshmi and U. B. Desai, in Proc. of the IEEE 4th World Forum on Internet of Things (WF-IoT), Singapore, 2018, pp. 609-614.

[111] S. D. Khirade and A. B. Patil, “Plant disease detection using image processing,” in Proc. of the International Conference on Computing Communication Control and Automation, January, 2015, pp. 768-771.

[112] C. G. Dhaware and K. H. Wanjale, “A modern approach for plant leaf disease classification which depends on leaf image processing,” in Proc. of the International Conference on Computer Communication and Informatics (ICCCI), January, 2017, pp. 1-4.

[113] S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using deep learning for image-based plant disease detection,” Frontiers in Plant Science, vol. 7, no. 1419, 2016.

[114] S. Huh, S. Cho, and S. Kim, “Managing IoT devices using blockchain platform,” in Proc. of the 19th international conference on advanced communication technology (ICACT), February, 2017, pp. 464-467.

[115] A. Dorri, S. S. Kanhere, R. Jurdak, and P. Gauravaram, “Blockchain for IoT security and privacy: The case study of a smart home,” in Proc. Of the IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), March, 2017, pp. 618-623.

[116] D. Knezevic, “Impact of Blockchain Technology Platform in Changing the Financial Sector and Other Industries,” Montenegrin Journal of Economics, vol. 14, pp. 109-120, 2018.

[117] F. Ferrández-Pastor, J. García-Chamizo, M. Nieto-Hidalgo, and J. Mora-Martínez, “Precision Agriculture Design Method Using a Distributed Computing Architecture on Internet of Things Context,” Sensors, vol. 18, no. 6, 2018.

[118] G. Vox, M. Teitel, A. Pardossi, A. Minuto, F. Tinivella and E. Schettini, "Sustainable greenhouse systems," in Sustainable Agriculture, Nova Science Publishers, 2010, pp. 1-79.

[119] D. Massa, L. Incrocci, R. Maggini, G. Carmassi, C. A. Campiotti and A. Pardossi, "Strategies to decrease water drainage and nitrate emission from soilless cultures of greenhouse tomato," Agricultural Water Management, vol. 97, pp. 971-980, 2010.

[120] D. Savvas and D. Passam, Hydroponic Productions of Vegetables and Ornamentals, Athens (GR): Embryo Publications, 2002.

[121] R. Thompson, L. Incrocci, W. Voogt, A. Pardossi and J. Magán, "Sustainable irrigation and nitrogen management of fertigated vegetable crops," Acta Horticulturae, vol. 1150, pp. 363-378, 2017.

[122] C. Emerson, "Water and Nutrient Reuse within Closed Hydroponic Systems," M.sc. thesis, Statesboro, 2014.

[123] J. Thornley and I. Johnson, Plant and crop modelling. A mathematical approach to plant and crop physiology, Oxford: Clarendon Press, 1990.

[124] Karuna Chandraul, Archana Singh,”An agriculture application research on cloud computing”, International Journal of Current Engineering and Technology, volume 3, No.5, pp. 2084-2087, October 2010.

[125] Ronald Haley, Riley Wortman, Yiannis Ampatzidis, Matthew Whiting, “An Integrated cloud-based platform for labor monitoring and data analysis in precision agriculture”, IEEE 14th International Conference on Information Reuse and Integration, pp. 349-356, August 2013.

[126] Mistsuyoshi Hori, Eiji Kawashima, Tomihiro Yamazaki," Application of cloud Computing to agriculture and prospects in other fields", FUJITSU Sci. Tech. J., volume 46, No. 4, October 2010.

[127] B. K. Jha, S. K. Jha, R. Mukaharjee, D. Basak, "Development of guided SMS solution in local language for Demand-driven Access of agriculture information", 7th International Conference on Communication Systems and Networks (COMSNETS), pp. 1-5, January 2015.

[128] D. D. Chaudhary, S. P. Nayse, L. M. Waghmare, "Application of wireless sensor network for greenhouse parameter control in precision agriculture", International Journal of Wireless and Mobile Networks (IJWMN), volume 3, No.1, 2011.

[129] O. T. Denmead and R. H. Shaw, "Availability of soil water to plants as affected by soil moisture content and meteorological conditions", Agronomy journal, 1962.

[130] Ahmad Nizar Harun, Mohamed Rawidean Mohd Kassim, Ibrahim Mat, Siti Sarah Ramli, "Precision Irrigation using Wireless Sensor Network", International Conference on Smart Sensors and Application (ICSSA), 2015.

[131] Narayut Putjaika, Sasimanee Phusae, Anupong Chen-lm, Dr. Phond Phunchongharm, and Dr. Khajonpong Akkarajitsakul, "A Control System in an Intelligent Farming by using Arduino Technology", Fifth ICT international Student Project Conference (ICT-ISPC), 2016.

[132] ZOU Cheng-jun, "Research and Implementation of Agricultural Environment Monitoring based on Internet of Things", Fifth International Conference on Intelligent Systems Design and Engineering Applications, 2014.

[133] Meonghun Lee, Jeonghwan Hwang, and Hyun Yoe, "Agriculture Production System based on IoT"

[134] , IEEE 16th International Conference on Computational Science and Engineering, 2013.

[135] FuBing, "Research on the Agriculture Intelligent system Based on IoT", International conference on Image Analysis and Signal Processing (IASP), page 1-4, 2012.

[136] Sanbo Li, “Application of the Internet of Things technology in precision agriculture irrigation systems”, International Conference on Computer Science and Service System, 2012.

[137] Ji-chun Zhao, and Jun-feng Zhang; Yu Feng ; Jian-xin Guo, “The Study and Application of the IoT Technology in Agriculture”, 3rd International conference on computer science and information technology, volume 2, page 462-465, 2010.

[138] R. Rajeswari; K. Suthendran and K. Rajakumar, “A Smart Agricultural Model by Integrating IoT, Mobile and Cloud-based Big Data Analytics”. International Conference on Intelligent Computing and Control (I2C2). v. 118, no 82018, pp. 365-370, 2017.

[139] J. P. Coelho and J. R. Silva, “Agricultura de Precisão”, 1st edition. ISBN 978-989-8319-04-3, Lisboa, Portugal, 2009.

[140] A. Tzounis, N. Katsoulas, T. Bartzanas, C. Kittas, “Internet of Things in agriculture, recent advances and future challenges” Biosystems Engineering, v. 164, pp. 31-48, December, 2017.

[141] N. Dlodlo, J. Kalezhi “The Internet of Things in Agriculture for Sustainable Rural Development” 2015 International Conference on Emerging Trends in Networks and Computer Communications (ENTCC), Windhoek, Namibia, May, 2015.

[142] P. P. Jayaraman, A. Yavari, D. Georgakopoulos, A. Morshed and A. Zaslavsky, “Internet of Things Platform for Smart Farming: Experiences and Lessons Learnt”. Sensors 2016, v. 16, pp. 1884. [6] Maia, R. F.; Netto, I.; Tran, A. L. H. “Precision Agriculture Using Remote Monitoring Systems In Brazil” IEEE Global Humanitarian Technology Conference (GHTC), San Jose, CA, USA, 25 December 2017.

[143] S. Li “Application of the Internet of Things Technology in Precision Agriculture Irrigation Systems”, 2012 International Conference on Computer Science and Service System, Nanjing, China, August, 2012.

[144] B. G. L. Dias, A. D. Coelho, W. O. Assis, F. A. Martins, R. C. Pires, “Monitoramento de Sensores de Umidade do Solo com Internet das Coisas (IoT)

Aplicado na Agricultura de Precisão” 11° Seminário Mauá de Iniciação Científica, São Caetano do Sul, SP, Brasil, 2019.

[145] G. Bitella, R. Rossi, R. Bochicchio, M. Perniola, and M. Amato, “A Novel Low-Cost Open-Hardware Platform for Monitoring Soil Water Content and Multiple Soil-Air-Vegetation Parameters”. Sensors 2014, v. 14, pp. 19639-19659.

[146] J. Ma, X. Zhou, S. Li, Z. Li, “Connecting Agriculture to the Internet of Things through Sensor Networks”, 2011 International Conference on Internet of Things and 4th International Conference on Cyber, Physical and Social Computing, Dalian, China, October, 2011.

[147] Usmonov, M.; Gregoretti, F. “Design and Implementation of a LoRa Based Wireless Control for Drip Irrigation Systems” 2nd International Conference on Robotics and Automation Engineering, 2017. [12] Zhao, W.; Lin, S.; Han, J.; Xu, R.; Hou, L. “Design and Implementation of Smart Irrigation System Based on LoRa” IEEE Globecom Workshops, Singapore, 4-9 December, 2017.

[148] A. Mukherjee, S. Misra, and N. S. Raghuwanshi, “A survey of unmanned aerial sensing solutions in precision agriculture,” Journal of Network and Computer Applications, vol. 148, p. 102461, 2019.

[149] I. Mahjri, A. Dhraief, A. Belghith, S. Gannouni, I. Mabrouki, and M. AlAjlan, “Collision risk assessment in flying ad hoc aerial wireless networks,” Journal of Network and Computer Applications, vol. 124, pp. 1 – 13, 2018.

[150] L. Yunling, X. Zili, L. Na, X. Shuxiang, and Y. Gang, “A path planning algorithm for plant protection uav for avoiding multiple obstruction areas,” IFAC-PapersOnLine, vol. 51, no. 17, pp. 483 – 488, 2018, 6^{th} IFAC Conference on Bio-Robotics BIOROBOTICS 2018.

[151] J. Zhang, Y. Wu, W. Liu, and X. Chen, “Novel approach to position and orientation estimation in vision-based uav navigation,” IEEE Transactions on Aerospace and Electronic Systems, vol. 46, no. 2, pp. 687–700, April 2010.

[152] D. Klein, S. Venkateswaran, J. Isaacs, J. Burman, T. Pham, J. Hespanha, and U. Madhow, “Localization with sparse acoustic sensor network using uavs as

information-seeking data mules," ACM Transactions on Sensor Networks (TOSN), vol. 9, 05 2013.

[153] G. Danoy, M. R. Brust, and P. Bouvry, "Connectivity stability in autonomous multi-level uav swarms for wide area monitoring," in Proceedings of the 5th ACM Symposium on Development and Analysis of Intelligent Vehicular Networks and Applications, ser. DIVANet '15. New York, NY, USA: ACM, 2015, pp. 1–8.

[154] E. Camci, D. R. Kripalani, L. Ma, E. Kayacan, and M. A. Khanesar, "An aerial robot for rice farm quality inspection with type-2 fuzzy neural networks tuned by particle swarm optimization-sliding mode control hybrid algorithm," Swarm and Evolutionary Computation, vol. 41, pp. 1 – 8, 2018.

[155] D. Cavaliere and S. Senatore, "Towards an agent-driven scenario awareness in remote sensing environments," 2018 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 1982–1989, 2018.

[156] J. Senthilnath, A. Dokania, M. Kandukuri, R. K.N., G. Anand, and S. Omkar, "Detection of tomatoes using spectral-spatial methods in remotely sensed rgb images captured by uav," Biosystems Engineering, vol. 146, pp. 16 – 32, 2016, special Issue: Advances in Robotic Agriculture for Crops.

[157] S. Zhang, G. Zhao, K. Lang, B. Su, X. Chen, X. Xi, and H. Zhang, "Integrated satellite, unmanned aerial vehicle (uav) and ground inversion of the spad of winter wheat in the reviving stage," Sensors, vol. 19, p. 1485, 03 2019.

[158] S. Cheng, Y. Li, Z. Tian, W. Cheng, and X. Cheng, "A model for integrating heterogeneous sensory data in iot systems," Computer Networks, vol. 150, pp. 1 – 14, 2019.

[159] M. Mahmoodpour and A. Lobov, "A knowledge-based approach to the iot-driven data integration of enterprises," Procedia Manufacturing, vol. 31, pp. 283 – 289, 2019, research. Experience. Education. 9th Conference on Learning Factories 2019 (CLF 2019), Braunschweig, Germany.

[160] G. Song, M. Wang, X. Ying, R. Yang, and B. Zhang, "Study on precision agriculture knowledge presentation with ontology," AASRI Procedia, vol. 3, pp. 732 – 738, 2012, conference on Modelling, Identification and Control.

[161] H. Ngo, N.-A. Le-Khac, and T. Kechadi, Ontology Based Approach for Precision Agriculture: 12th International Conference, MIWAI 2018, Hanoi, Vietnam, November 18–20, 2018, Proceedings, 11 2018, pp. 175–186.

[162] A. R. Muljarto, J.-M. Salmon, B. Charnomordic, P. Buche, A. Tireau, and P. Neveu, "A generic ontological network for agri-food experiment integration – application to viticulture and winemaking," Computers and Electronics in Agriculture, vol. 140, pp. 433 – 442, 2017.

[163] D. Vallejo, J. Castro-Schez, C. Glez-Morcillo, and J. Albusac, "Multiagent architecture for information retrieval and intelligent monitoring by uavs in known environments affected by catastrophes," Engineering Applications of Artificial Intelligence, vol. 87, p. 103243, 2020.

[164] F. Bu and X. Wang, "A smart agriculture iot system based on deep reinforcement learning," Future Generation Computer Systems, vol. 99, pp. 500 – 507, 2019.

[165] W. Mendes, F. Ara´ujo, and S. Er-Raki, Integrating Remote Sensing Data into Fuzzy Control System for Variable Rate Irrigation Estimates, 06 2019.

[166] R. Lokers, R. Knapen, S. Janssen, Y. van Randen, and J. Jansen, "Analysis of big data technologies for use in agro-environmental science," Environmental Modelling & Software, vol. 84, pp. 494 – 504, 2016.

[167] A. Kamilaris, F. Gao, F. X. Prenafeta-Boldu, and M. I. Ali, "Agriiot: A semantic framework for internet of things-enabled smart farming applications," in 2016 IEEE 3rd World Forum on Internet of Things (WF-IoT), Dec 2016, pp. 442–447.

[168] A. Starkey, H. Hagras, S. Shakya, and G. Owusu, "A multi-objective genetic type-2 fuzzy logic-based system for mobile field workforce area optimization," Information Sciences, vol. 329, pp. 390 – 411, 2016, special issue on Discovery Science.

[169] T. Popovic, N. Latinović, A. Pesic, Z. Zecevic, B. Krstajic, S. Đukanović (2017): Architecting an IoT-enabled platform for precision agriculture and ecological

monitoring: A case study. Computers and Electronics in Agriculture. 2017. 255-265. 10.1016/j.compag.2017.06.008.

[170] S. Jaiswal, V. Bhadoria, A. Agrawal, H. Ahuja (2019): Internet Of Things (Iot) For Smart Agriculture And Farming In Developing Nations. International Journal of Scientific & Technology Research. 8. 1049- 1058.

[171] N. G. Shah, I. Das, Precision Irrigation (2012): Sensor Network Based Irrigation. Problems, Perspectives and Challenges of Agricultural Water Management, InTech

[172] A. Matese, S. F. Di Gennaro (2015): Technology in precision viticulture: a state of the art review. Volume 2015:7 Pages 69—81, DOI :10.2147/IJWR.S69405

[173] J.E. Aho (2002): NASA providing new perspectives on vineyard management. Vineyard and Winery Management. 28(4):74–77.

[174] J. Arnó (2008): Variabilidad Intraparcelaria en Viña y uso de Sensores Láser en Viticultura de Precisión [doctoral thesis]. [Laser sensor in Precision Viticulture to describe intra-field variability in the vineyard] Lleida: University of Lleida, Spanish.

[175] J. Arnó, X. Bordes, M. Ribes-Dasi, R. Blanco, J.R. Rosell (2005): Esteve J. Obtaining grape yield maps and analysis of within-field variability in Raimat (Spain). Proceedings of the 5th European Conference on Precision Agriculture June 8–11, Uppsala, Sweden. 899–906.

[176] R.G.V. Bramley, A.P.B. Proffitt, R.J. Corner, T.D. Evans (2000): Variation in grape yield and soil depth in two contrasting Australian vineyards. Australian and New Zealand Second Joint Soils Conference; December 3–8, Lincoln, New Zealand. 29–30.

[177] R. Bramley (2003): Smarter thinking on soil survey. Australian and New Zealand Wine Industry Journal. 18(3):88–94.

[178] R.G.V. Bramley, D.W. Lamb (2003): Making sense of vineyard variability in Australia. Proceedings IX Congreso Latinoamericano de Viticultura y Enología. November 24–28, Santiago, Chile. 35–54.

[179] R.G.V. Bramley (2001): Progress in the development of precision viticulture – variation in yield, quality and soil properties in contrasting Australian vineyards. In: Currie LD, Loganathan P, editors. Precision Tools for Improving Land Management: Proceedings of the Workshop held by the Fertilizer and Lime Research Centre in Conjunction with the NZ Centre for Precision Agriculture at Massey University, Palmerston North, New Zealand, 14–15 February, 25–43.

[180] R.G.V. Bramley, S.K. Williams (2001): A protocol for winegrape yield maps. Proceedings of the 3rd European Conference on Precision Agriculture. June 18–21, Montpellier, France, 773–778.

[181] R.G.V. Bramley, R.P. Hamilton (2004): Understanding variability in winegrape production systems. 1. Within vineyard variation in yield over several vintages. Australian Journal of Grape and Wine Research 10: 32-45.

[182] R.G.V. Bramley, R.P. Hamilton (2007): Terroir and Precision Viticulture: are they compatible. J. Int. Sci. Vigne Vin, 41(1):1-8.

[183] J. Carothers (2000): Imagery technology meets vineyard management. Practical Winery and Vineyard, 21(1):54–62.

[184] C. Penn (1999): Grape growers gravitating toward space age technologies. In Wine Business, Monthly, Wine Communications Group, Sonoma, CA, USA.

[185] J.A. Taylor (2004): Digital Terroirs and Precision Viticulture: Investigations into the Application of Information Technology in Australian Vineyards [doctoral thesis]. Sydney: University of Sydney.

[186] B. Tisseyre, C. Mazzoni, N. Ardoin, C. Clipet (2001): Yield and harvest quality measurement in precision viticulture – application for a selective vintage. Proceedings of the 3rd European Conference on Precision Agriculture. June 18–21, Montpellier, France. 133–138.

[187] G. Ozdemir, A. Sessiz, F. G. Pekitkan (2017): Precision Viticulture tools to production of high quality grapes. Scientific Papers. Series B, Horticulture. Vol. LXI, 2017, ISSN 2285-5653

[188] D. S. Gurjar (2019): Precision irrigation management: concepts and applications for higher use efficiency in field crops. In book: Scaling water productivity and

resource conservation in upland field crops ensuring more crop per drop- a training manual, ICAR-IIPR, Kanpur

[189] S. Khriji, D. El Houssaini, M. W. Jmal, C. Viehweger, M. Abid, O. Kanoun (2014): Precision irrigation based on wireless sensor network", IET Sci. Meas. Technol., , Vol. 8, Iss. 3, pp. 98–106, doi: 10.1049/ietsmt. 2013.0137

[190] Kassim, Mohamed Rawidean Mohd, Ibrahim Mat, and Ahmad Nizar Harun. "Wireless Sensor Network in precision agriculture application." International Conference on Computer, Information and Telecommunication Systems (CITS), 2014. IEEE, 2014.

[191] Lee, In, and Kyoochun Lee. "The Internet of Things (IoT): Applications, investments, and challenges for enterprises." Business Horizons 58.4 (2015): 431-440.

[192] Kodali, Ravi Kishore, and Nisheeth Rawat. "Wireless sensor network in mango farming." IEEE Nirma University International Conference on Engineering (NUiCONE), 2013. IEEE, 2013.

[193] Prathyusha, K., G. Sowmya Bala, and K. Sreenivasa Ravi. "A real-time irrigation control system for precision agriculture using wsn in Indian agricultural sectors." International Journal of Computer Science, Engineering and Applications 3.4 (2013): 75.

[194] Kim, Yunseop, Robert G. Evans, and William M. Iversen. "Remote sensing and control of an irrigation system using a distributed wireless sensor network." IEEE transactions on instrumentation and measurement 57.7 (2008): 1379-1387.

[195] Slijepcevic, Sasha, and Miodrag Potkonjak. "Power efficient organization of wireless sensor networks." IEEE International Conference on Communications, 2001. ICC 2001. Vol. 2. IEEE, 2001.

[196] Pottie, Gregory J. "Wireless sensor networks." Information Theory Workshop, 1998. IEEE, 1998.

[197] R. Gebbers and V. I. Adamchuk, "Precision agriculture and food security," Science, vol. 327, no. 5967, pp. 828–31, Feb. 2010.

[198] R. Bongiovanni and J. Lowenberg-Deboer, “Precision agriculture and sustainability,” Precision Agriculture, vol. 5, no. 4. pp. 359–387, 2004.

[199] N. Zhang, M. Wang, and N. Wang, “Precision agriculture - A worldwide overview,” in Computers and Electronics in Agriculture, 2002, vol. 36, no. 2–3, pp. 113–132.

[200] L. Atzori, A. Iera, and G. Morabito, “The Internet of Things: A survey,” Comput. Networks, vol. 54, no. 15, pp. 2787–2805, Oct. 2010.

[201] D. Bandyopadhyay and J. Sen, “Internet of things: Applications and challenges in technology and standardization,” in Wireless Personal Communications, 2011, vol. 58, no. 1, pp. 49–69.

[202] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, “Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications,” IEEE Commun. Surv. Tutorials, vol. 17, no. 4, pp. 2347–2376, Oct. 2015.

[203] J. A. Stankovic, “Research directions for the internet of things,” IEEE Internet Things J., vol. 1, no. 1, pp. 3–9, Feb. 2014.

[204] N. Dlodlo and J. Kalezhi, “The internet of things in agriculture for sustainable rural development,” in 2015 International Conference on Emerging Trends in Networks and Computer Communications (ETNCC), 2015, pp. 13–18.

[205] J. Ma, X. Zhou, S. Li, and Z. Li, “Connecting Agriculture to the Internet of Things through Sensor Networks,” in 2011 International Conference on Internet of Things and 4th International Conference on Cyber, Physical and Social Computing, 2011, pp. 184–187.

[206] S. S. H. Hajjaj and K. S. M. Sahari, “Review of agriculture robotics: Practicality and feasibility,” IRIS 2016 - 2016 IEEE 4th Int. Symp. Robot. Intell. Sensors Empower. Robot. with Smart Sensors, no. December 2016, pp. 194–198, 2017.

List of Publication

1. Rokade, A., Singh, M., Malik, P. K., Singh, R., & Alsuwian, T. (2022). Intelligent Data Analytics Framework for Precision Farming Using IoT and Regressor Machine Learning Algorithms. *Applied Sciences*, *12*(19), 9992.

2. Rokade, A., Singh, M., Arora, S. K., & Nizeyimana, E. (2022). IOT-Based Medical Informatics Farming System with Predictive Data Analytics Using Supervised Machine Learning Algorithms. *Computational and Mathematical Methods in Medicine*, *2022*.

3. Rokade, A., & Singh, M. (2021, October). Analysis of precise green house management system using machine learning based Internet of Things (IoT) for smart farming. In *2021 2nd International Conference on Smart Electronics and Communication (ICOSEC)* (pp. 21-28). IEEE.

4. Rokade, A., & Singh, M. (2023). Smart Farming System Based on IoT for Precision Controlled Greenhouse Management. In *Computational Intelligence: Select Proceedings of InCITe 2022* (pp. 435-443). Singapore: Springer Nature Singapore.

5. "An Autonomous Smart Farming System for Computational Data Analytics using IoT." AI Rokade, AD Kadu, KS Belsare - Journal of Physics: Conference Series, 2022.

RESUME

Ashay Indrabhan Rokade

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Student-centered facilitator with expertise in Object Oriented Programming and Data Communication. Offers nine-year background supporting students, developing instructional plans and organizing and grading exams and tests. Looking to apply extensive skills in project management and development at institute level. Expertise in inspirational and motivational speaking with continuous learning ability. Seeking for the opportunity to work with the good organization for personal growth.

- **Skills**

Project Management, Resource Management, Public Speaking, Team Management, Programming
Languages, MS Office, Counseling, Research Guidance.

- **Work history**

June 2014 – Till Date (9 Years and 6 Months)

Assistant Professor
Prof. Ram Meghe Institute of Technology & Research, Badnera.

- Applied innovative teaching methods to encourage student learning objectives.
- Taught programming languages with hands on sessions.
- Conducted various programs and delivered various guest lectures for student development.
- Participated and Presented research articles in Scopus indexed conferences and published research article in Scopus and SCI Journals.
- Built strong rapport with students through class discussions and academic advisement.
- Worked in Various Institutional and Departmental Committees like NSS, Youth Festival, etc.
- Contributed to planning appropriate and engaging lessons for both classroom and distance learning applications.
- Performed research to serve as basis for academic writing for publication.

- **Education**

Sr. No.	University/ Board	Educational Qualification	Division/ Class	Year	Field of Specialization	Percentage
1	L.P.U, Phagwara, Punjab.	**Ph.D**		2020	Wireless Communication	Pursuing
2	YCMOU, Nashik.	**M**aster of **B**usiness **A**dministration	First Class	2018	Human Resource Management	71.8%
3	JNTU, Hyderabad.	**M**aster of **Tech**nology	Distinction	2014	Embedded Systems	79.50%
4	Dr. B.A.M.U, Aurangabad.	**B**achelor of **E**ngineering	Distinction	2011	Industrial Electronics	67.02%
5	MSBTE	**Diploma**	First Class	2007	Electronics	66.32%
6	Amravati	**SSC**	First Class	2004	-	64.26%

- **Interests**

Wireless Communication, Embedded Systems, Project Management, Human Resource Management, Public Speaking, Personal Growth.

- **Publications (Scopus/SCI):**

Sr. No.	Title of the Paper	Journal Details	Indexing
1	Intelligent Data Analytics Framework for Precision Farming Using IoT and Regressor Machine Learning Algorithms	MDPI (Applied Sciences)	SCI
2	TOT-Based Medical informatics Farming System with Predictive Data Analytics Using Supervised Machine Learning Algorithms	Hindawi (Computational and Mathematical Methods in Medicine)	SCI

3	Analysis of Precise Green House Management System using Machine Learning based Internet of Things (IoT) for Smart Farming	IEEE Xplore (Proceedings of ICOSEC)	Scopus
4	An Autonomous Smart Farming System for Computational Data Analytics using IoT	Journal of Physics (ICICS-2022)	Scopus
5	Smart Farming System Based On internet of Things (IoT) for Precision Controlled Greenhouse Management.	Springer Nature Book Series	Scopus

- **Project Undertaken:**
    - Project Guided to UG Students: **15**
    - Project Guided to PG Students: **09**

- **Guest Lectures/Workshops:**
    - Guest Lectures Delivered: **27**
    - Workshop Organized: **05** (Personality Development)
    - Workshop/STTP/FDP Attended: **23**

- **Other Educational Qualifications**
    - **Certified MCED Trainer (On MCED Empanelment)**
    - Bachelor of Arts in Psychology
    - Diploma in Journalism
    - Certification in Human Rights
    - MS-CIT

- **Membership of Scientific and Professional Societies:**

Sr. No.	Name of Professional Body	Type of Membership	Membership No.
1.	ISTE	Member	LM-81984
2.	IEI	Asso. Member	AM-147605-2

Ashay Indrabhan Rokade
Asst. Professor
(EXTC)
PRMIT&R, Badnera.

Annexure I

1. Circuit Diagram: Proposed experimental model with sensor specifications

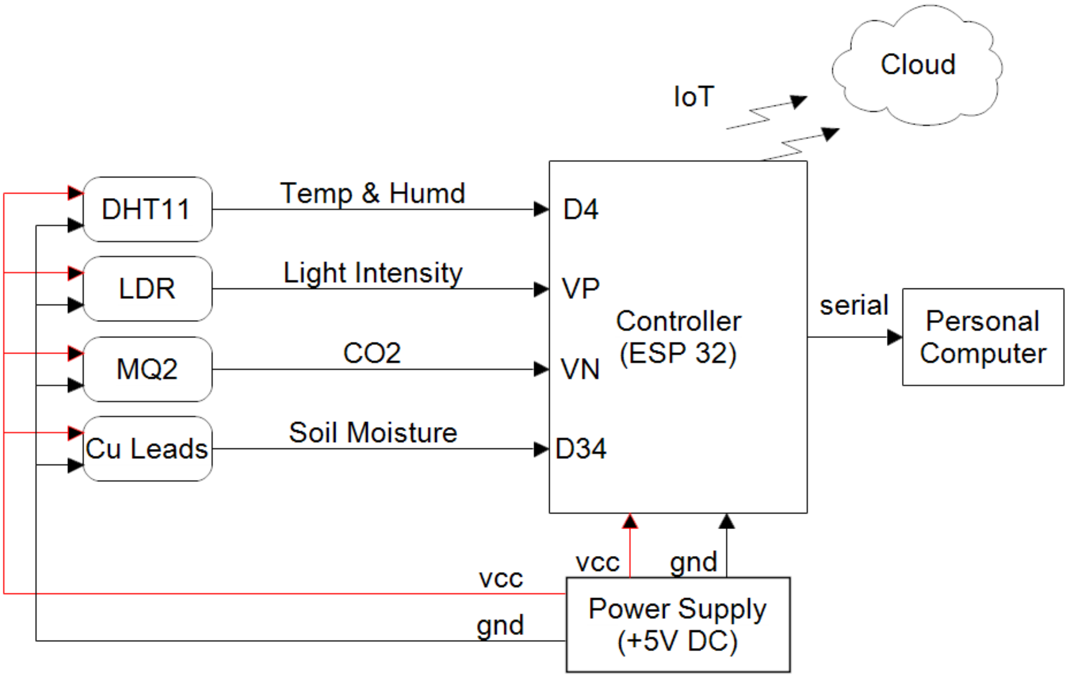

Figure: Circuit diagram of proposed system for data acquisition.

Annexure II

1. Certificate of Visit And Data Collection.

COLLEGE OF AGRICULTURE, PUNE.

University Road, Narveer Tanaji Wadi, Shivaji Nagar, Ganeshkhind Road,
Pune, Maharashtra 411005.
Est 1907

Website: www.acpune.in

CAP/DHL/04/09/2021

Date: 06/09/2021

CERTIFICATE

This is to certify that Ashay Indrabhan Rokade, PhD Scholar from School of Electrical and Electronics Engineering of Lovely Professional University, Phagwara, Punjab bearing Reg. No. 41900712 has interacted with the professionals on his PhD Topic 'Development of Precision Controlled Green House Management System Using Machine Learning Enabled Internet of Things' under the guidance of Dr. Manwinder Singh, Associate Professor, School of Electrical and Electronics Engineering of Lovely Professional University, Phagwara, Punjab.

The Cultivation Process for Gerbera and Broccoli were Discussed and Primary Data for the same has been given to the PhD Scholar.

Project Incharge
Hi-Tech Research
College of Agriculture, Pune.

Dr. Sachin Chavhan
Project Incharge
Hi-Tech Research center
Department of Horticulture
College of Agriculture, Pune.

2. Questionnaire for Reference Data Set of Gerbera and Broccoli

Questionnaire for Gerbera and Broccoli Cultivation

By:

Ashay Indrabhan Rokade
PhD Scholar
School of Electrical and Electronics Engineering,
Lovely Professional University, Phagwara, Punjab. (India).

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Gerbera Cultivation:

Soil Requirement and Treatment:

1. Depth of Penetration of Root of the Plant (cm): **50-70 Cm**
2. Type of Soil Required : **Highly Porous and Well Drained**
3. pH Level of the Soil :**5.5 to 6.5**
4. The Salinity Level of the Soil (ms/cm): **<1**

Green House Arrangement:

1. The Temperature within the greenhouse for initiation:**23° C**
2. The Temperature within the greenhouse for unfolding of the leaves:**25-27 ° C**
3. Temperature Range: Minimum **12 ° C** And Maximum **35 ° C**
4. The Optimum humidity within the greenhouse:**70-75%**
5. Minimum Height of the Greenhouse:**5 to 6.5 m**
6. The Thickness of the polythene: **200 Microns**
7. Gutter Direction of Greenhouse:**North South**
8. Does ventilation Required:**Yes**

Bed Preparation:

1. Height of the bed:**1.5 ft**(45-50 cm Approx)
2. Width of the bed:**2 ft**(65-70 cm Approx)
3. Spacing Between the Beds:**1 ft**(30-35 cm Approx)
4. Humidity of the Greenhouse after planting:**80-90%** (4-6 Weeks) to avoid desiccation.

Irrigation Requirement:

1. Water pH:**6.5 to 7**
2. Water EC:**<0.~~7~~5ms/cm**
3. Water Hardness:**200 ppm**
4. Water T D S**~~4~~350 ppm**
5. Time to take final production:**75-90 Days**

Dr. Sachin Chavhan
Project Incharge
Hi-Tech Research Center
Horticulture, College of Agriculture, Pune.

Figure: Questionnaire Scan Copy for Gerbera Cultivation

Questionnaire for Gerbera and Broccoli Cultivation

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Broccoli Cultivation:

Soil Requirement and Treatment:

1. Depth of Penetration of Root of the Plant (cm): **50-70 Cm**
2. Type of Soil Required : **Sandy and Silt loam**
3. pH Level of the Soil :**5.5 – 6.5**
4. The Salinity Level of the Soil (ms/cm): -

Green House Arrangement:

5. The Temperature within the greenhouse at Day Time:**25 ° C – 26 ° C**
6. The Temperature within the greenhouse at Night Time:**16 ° C – 17 ° C**
7. Temperature Range: Minimum **12° C** And Maximum **30 ° C**
8. The Optimum humidity within the greenhouse:**70-75%**
9. Minimum Height of the Greenhouse:- 6.0 – 6.5 m
10. The Thickness of the polythene: - 200 micron
11. Gutter Direction of Greenhouse: - North South
12. Does ventilation Required:**Yes**

Bed Preparation:

13. Height of the bed: 45 cm
14. Width of the bed: 75 cm
15. Spacing Between the Beds: 50 cm
16. Humidity of the Greenhouse after planting: 80%

Irrigation Requirement:

17. Water pH: - 7.0
18. Water EC: - Up to 0.5 ms
19. Water Hardness: - 200 ppm
20. Water T D S: - 350 ppm
21. Time to take final production:**100-115 Days**

Dr. Sachin Chavhan
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3. Field Visit Photographs

Greenhouse Environment (Outside)

Greenhouse Environment (Inside)

Field Visit for Reference Data