Chapter 2
Literature Survey

2.1 INTRODUCTION

With the intention of increasing agricultural field productivity, crop performance must be understood and anticipated across a wide range of natural soil quality, fertilization, and irrigation circumstances. Knowing which crop combination has produced the best results under similar soil, environment, fertilization, and irrigation conditions could increase the efficiency of an agricultural field in all aspects like yield progress, yield quality, etc. Similar information systems to crop selection can also apply to environmental variation, asset constraints (such as water quality and energy deficiencies), and societal concerns over matters like animal health, manure, and the environment, which occasionally have an impact on agricultural output. As the water is a noteworthy natural content. Smart utilization of water requires accurate prediction of wetness inside the farm. Various Internet of Things (IoT) based researches is executed for smart irrigation to save water as well as crops (kim et al. 2018).

Utilizing information and communication technologies (ICT), particularly the Internet of Things (IoT) and related extensive data analytics, smart farming involves managing these issues through electronic yield monitoring as well as related environmental, land preparation, and water system conditioning. Such tracking data can then be analyzed to determine which plants and particular crop varieties best match the production goals of any given farm anywhere in the world.

Crop diseases have an impact on the progress of their particular species, hence early detection is crucial. For the identification and classification of plant diseases, numerous Machine Learning models have been employed. However, with the development of a subset of Machine Learning (ML) called Deep Learning (DL), this field of study now appears to have significant potential in terms of improved accuracy. In order to detect as well as categorize the signs of plant diseases, several developed/modified DL architectures are used in conjunction with a number of visualization techniques. Additionally, a number of performance indicators are employed to assess these structures and methodologies. Additionally, several study gaps are noted from which to acquire greater transparency for spotting plant illnesses even before they manifest themselves. Thus, the combination of ICT system employing ML and DL methods improve the performance of a system in smart farming.

2.2 BACKGROUND

2.2.1 Precision Agriculture

A way of controlling agricultural packages known as precision agriculture (PA) first appeared in the USA in the 1980s. Researchers from Minnesota University changed the calcium intake on agricultural plots in 1985. The experimental process entails the application of certain inputs (nitrogen (N), phosphorus (P), and potassium (K)) in high energy concentration yields as well as inputs like maize and sugar beet in the context of the struggle to improve agricultural yields.

PA farming focuses mostly on increasing yields and returns while looking for a better explanation for the environment's irregularity and adjusting conditions between dissimilar farms. Spadework, fertilization, seeding, irrigation, and pesticide spraying have all been impacted by PA.

2.2.2 Internet of Things (IoT)

IoT refers to a scheme of interconnected various components which have some computational efficiency, advanced equipment, etc. those are labeled with sole personalities which can communicate all around the world and do not require any kind of human intervention. the Internet of Things is a method which encapsulates the software and hardware components with each other, and facilitates the society.

Many industrial fields, including PA, infrastructure development, medical issues, conveyance, and many more, use IoT technology.

2.3 RECENT RESEARCH

Historically, population growth and socioeconomic conditions have been linked to food shortages (Slavin, 2016). No. of human beings on the earth has increased from approximately 3,000,000,000 to 6,000,000,000. over the past 50 years, increasing the additional requirement of farm products (Kitzes, et al., 2008).

According to predictions from the Food and Agriculture Organization of the United Nations (FAO, 2009), the figure of total no. of people on the earth would rise by around 30% in the next 30 years, necessitating an additional 70% requirement in agriculture yield. Food security, which is defined as everyone having access to enough, safe, and nourishing food, is uncertain due to variety of factors. (Gebbers & Adamchuk, 2010). This conventional agricultural system heavily depends on fossil fuels.

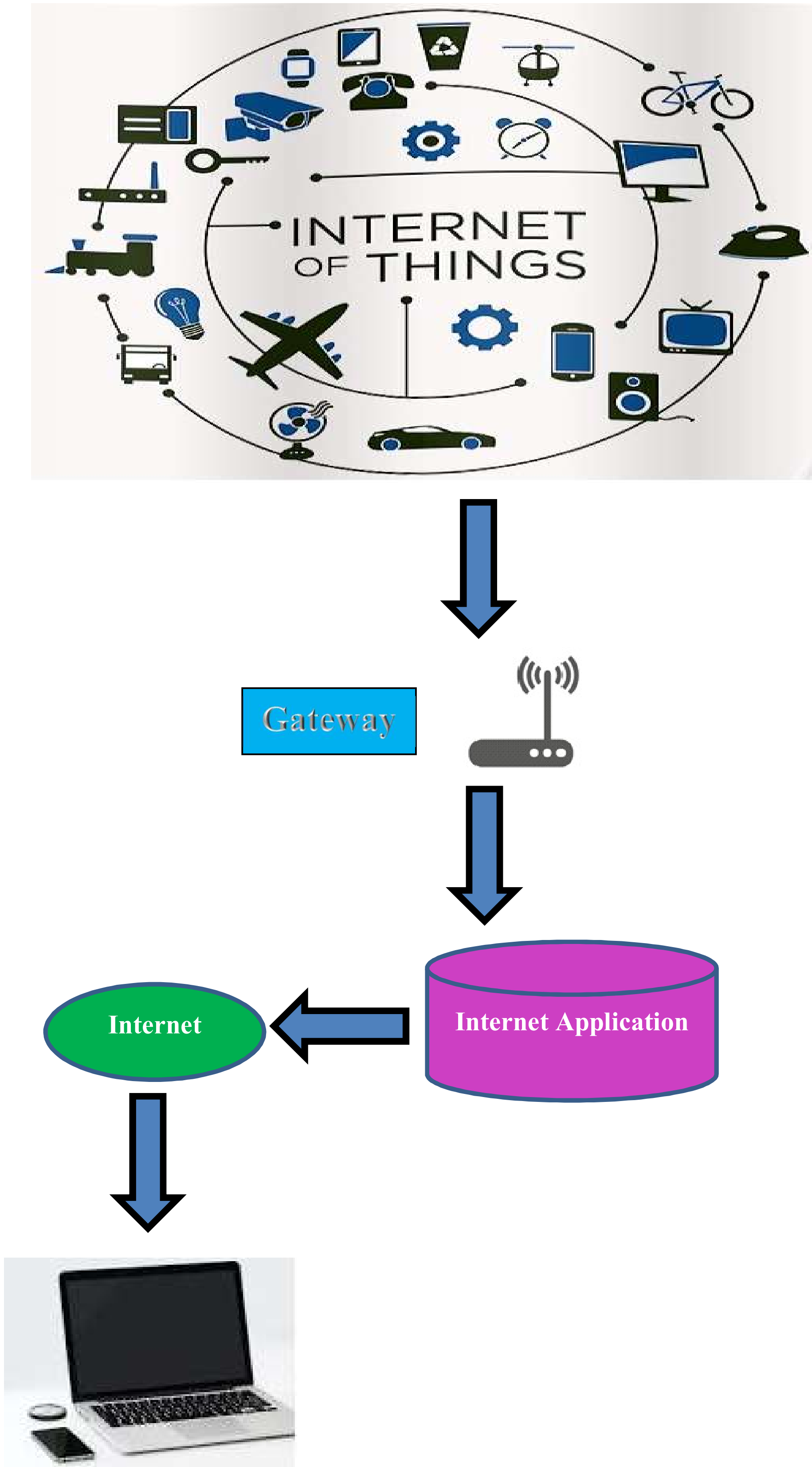

Figure 2.1 Straightforward Impression of IoT System

Due to these uncertainties, agriculture, which now produces 20% of all anthropogenic Greenhouse Gas (GHG) emissions, is under pressure to increase production while reducing its environmental impact (Sayer & Cassman, 2013). Since the 1990s, a number of research projects have been started in an effort to meet these growing demands. Precision agriculture is the practice of precisely localizing point dimensions in the turf so it is possible to develop spatial variability maps. (Pierce & N., 1999), thanks to developments in plant progress modelling as well as agriculture productivity nursing (B.B., et al., 2001) and global navigation satellite systems (e.g. GPS) (Bell, et al., 1995). Currently, biotechnology and new digital technologies like remote sensing (Bastiaanssen et al., 2000), cloud computing (Hashem et al., 2015), and the Internet of Things (IoT) (Weber & Weber, 2010) are supporting agricultural practices, giving rise to the concept of "smart farming" (Tyagi, 2016, Babinet, Gilles et al., 2015).

The use of innovative information and communication technologies (ICT) for small-scale farming to large-scale agriculture administration extends the concept of precision agriculture (Lokers et al., 2016), improving the supervision and administration by context (Kamilaris et al., 2016), circumstances and position alertness, and other tasks that are currently being done (Hira et al. 2020). The issues of farming productivity in terms of yield, influence on the environment, nutrition safety, and maintainability must be met via smart farming. agricultural intelligence (Bongiovanni & Lowenberg-DeBoer, 2004), is closely related to sustainable agriculture (Senanayake, 1991), which improves the resource base and environmental quality on which agriculture depends to meet fundamental food desires of human-being (Pretty, 2008). One can think of it as a fresh climate-based method of farming that fully combines the biological, chemical, physical, ecological, economic, and social disciplines with the purpose of creating secure, intelligent agriculture methods which cannot harm the climate. According to (McQueen, et al., 1995) and (Gebbers & Adamchuk, 2010), excellent knowledge regarding complex, multi-variate, and random farming environments is necessary, to report the problems with intelligent agriculture processes and excellent farming. By continuously monitoring and measuring different components of the physical environment as noted above, developing smart IoT based methods help to examine this (Ma Juncheng et al. (2015 a, b), Sonka, 2016). As a result, they generate massive amounts of information at an extraordinary rate (Chi, et al., 2016). According to (Hashem, et al., 2015), this indicates the requirement for massive data assortment, storing the information, pre-requisite of work, modelling, as well as scrutiny from numerous varied sources.

Agricultural "big data" necessitates significant savings in set-ups regarding data processing with storage (Nandyala & Kim, 2016; Hashem, et al., 2015), some of which must function virtually instantly (e.g., weather forecasting, animal and crop pest monitoring). Therefore, "big data analysis" is a novel and excellent approach (Kempenaar, et al., 2016, Sonka, 2016, Kamilaris et al. 2017 (a,b)), which is created to allow for high-velocity data capture, discovery, and/or analysis so that agronomists, as well as other stack-holders, may find their financial worth from it. Big data analysis has only recently been used in agriculture (Lokers et al., 2016), as investors began to recognize its possible aids (Bunge, 2014), while appearing to be successful and popular in many other fields (Sonka, 2016). Some of the biggest agricultural firms claim that giving farmers advice based on the analysis of big data may boost yearly worldwide crop profits by roughly US $20 billion (Bunge, 2014). The reason for creating this study is that big data investigation in smart farming is a contemporary method that is gaining in popularity and recent developments and advantages of big data in many different fields suggest that it has significant promise (Kim, et al., 2014). (Cooper, et al., 2013). Recent studies on the topic (Wolfert et al., 2017), (Nandyala & Kim, 2016), (Waga & Rabah, 2014), and (Wu, et al., 2016) primarily complete theoretic features of this practice (such as theoretical context, social-economic problems, commercial procedures), as well as they concentrate on a specific part like remote sensing (Chi, et al., 2016), (Liaghat & Balasundram 2010, Karmas, et al., 2016).

Bright Keswani et al. (2019) has developed a DSS in order to collect live data from the field by computing at a different place on the field, this proposed method depends on a self-governing, IoT aided system using sensors-based architecture made up of soil moisture (MC) probe, soil temperature measuring device, environmental temperature sensor, environmental humidity sensing device, CO2 sensor, and daylight intensity device (light dependent resistor). The study describes how to use irrigation as efficiently as possible by controlling water valves precisely and predicting the soil's need for water one hour in advance using neural networks.

The separate IoT aided sensors aimed at accurate information collection besides storing agricultural data to make up the predicted observance technique.

As a result, this survey's fundamental contribution is that, in contrast to previous studies in which investigation of real-time information is a crucial component and solving the problems discovered within the big data arena, it provides an additional attentive impression of the specific difficulties experienced regarding smart farming. The suggested research emphasizes the (big) data used, the methodologies besides methods used, providing particular technical insights on the benefits of big data analysis, as well as outstanding problems, roadblocks, and strategies to get through them. In a time when there is a greater need for food, PA offers better harvests at a lower cost and reduces ecological effort and affluence. However, a feedback scheme (DSS) has been established in the last ten years to provide farmers with the expert knowledge they want for crop supervision.

IoT and cloud computing are two key concepts that are currently emerging as a result of the development of ICT. These two ideas are anticipated to be used in agronomy on a larger scale in the future. Utilizing computer resources that can be installed and used from a distance, such as processing power, storage capacity, memory, inter-network, etc., is the foundation of cloud computing as shown in figure 2.1. Table 2.1 shows the list of a few research work on smart farming based on IoT concept.

2.3.1 Plant Diseases Identification

Plant disease is a dangerous and unavoidable problem in agriculture since it reduces productivity. In order to estimate yield and recommend action, one must first evaluate the severity of the plant disease. This is a critical measurable component in the field of agriculture. Because yield enhancement directly affects the nation's economy. Maize crop leaves have a great deal of illness and significant damage. The quick, truthful judgment of sick extremities will support to boosting production.

Traditionally, botanist scientists and professionals evaluated the severity of plant diseases through ongoing observation of plant tissue. This method is inefficient and extremely expensive as well as, time-consuming. The manual diagnosis of plant crop diseases is impeding contemporary agriculture's rapid expansion (F. Zhang, 2013). These days, crop disease diagnosis is completely automated because of the use of digital cameras and computer vision, prepared by clever DNN models using various methods. Therefore, the goal of the research is to totally automatically, fast, and flexibly classify plant diseases. The most widely grown crop and a major source of food is maize, with the exception of rice and wheat its overall yield is the highest on the planet (G. F. Sprague, 1955).

Sr. No.	Authors and year of publication	Work	Merits	Demerits
1.	Prathibha et al. (2017)	µC CC3200 Chip based system with few sensors used Wi-Fi to transmit MMS	Transmit Air temperature and Humidity	High cost Smart DSS unavailable
2.	Rao R. et al. (2018)	raspberry pi 3 base system transmitting moisture and temperature data on Google Cloud.	Saving of Water	Smart DSS unavailable
3.	Mishra D. et al. (2018) & Anupama et al. (2020)	Moisture sense by Arduino and transmitted on web server through Wi-Fi	Saving of Water	Smart DSS unavailable
4.	Kale A. et al. (2019)	Temperature, Humidity sensed by Arduino and transmitted through Wi-Fi	Feature Selection & Extraction Technique with IGAELM classifier	Water management unobtainable.
5.	dos Santos U.et al. (2019)	µC ATmega328 with few sensors	LoRa Technique, ARIMA based forecasting	Real Time monitoring Unavailable

Sr. No.	Authors and year of publication	Work	Merits	Demerits
6.	Alipio et al.	Arduino based system with few sensors. Transmitting data on ThingSpeak	Hydroponic System based on Bayesian Network with manual & Automatic control.	Computation cost is very high
7.	Nayyar A. et al. (2016)	Ardiuno based system with few sensors, transmitting data on ThingSpeak through Wi-Fi	Real Time monitoring is possible	Only Manual Control.
8.	Sales N. et al. (2015)	μC MSP4305419A and soil moisture sensor with Cloud Based WSAN System used ZigBee & GPRS	Utilizing Moisture to forecast weather and water irrigation controlled with reference value	Smart DSS not available
9.	Na A. et al. (2016)	μC STM32L152RE based system with few sensor and Bluetooth protocol	Sense precise parameter and also transmit it on cell phone through Bluetooth	Smart DSS not available

Sr. No.	Authors and year of publication	Work	Merits	Demerits
10.	Saraf S. et al. (2019)	µC Atmega328 based system with few sensors. Transmitting data on Apache Tomcat, HTTP web server with use of ZigBee.	Smart irrigation. Application developed on android platform	Smart DSS not available
11.	Benyezza et al. (2018)	Arduino UNO based system with few sensors, share data on ThingSpeak through Wi-Fi	Constant monitoring and governing of irrigation	Smart DSS not available
12.	Ananthi N. et al. (2017)	µC MCP3008based system with few sensor and Wi-Fi protocol	feedback about irrigation and fertilization	No Automation
13.	Lashitha et al. (2018)	Node MCU V3based system with few sensors. Transmitting data on ThingSpeak	Data continuously retrieved via ThingSpeak	Smart DSS unavailable
14.	Pallavi S. et. al. (2017)	IoT based system with few sensors deploying AWS cloud.	Preserve green house as per moisture condition	Smart DSS unavailable
15.	L. G. et al. (2017)	Arduino Mini Pro based system with few sensors transmitting data on Xively using Wi-Fi	water saving Crop nursing and pesticides control	Smart DSS unavailable

Sr. No.	Authors and year of publication	Work	Merits	Demerits
16.	Suma et al. (2017)	µC PIC16877A based system with few sensor and GSM Module	remote monitoring	Smart DSS unavailable
17.	Krishna K. et al. (2017)	Raspberry Pi 2 Model B based system with few sensors used ZigBee, Wi-Fi module	Pesticides are sprayed by a mobile robot.	Smart DSS unavailable
18.	Nikesh et al. (2016)	AVR based system with few sensors used ZigBee	Remote control robotic system	Smart DSS unavailable
19.	Sushanth G. et al. (2018)	Arduino based system with few sensors. sends data on Web server using Wi- Fi /3G /4G, GSM	Used Android application on cell phone for water irrigation control.	Smart DSS unavailable
20.	Lahande P. et al. (2018)	µC ATMEGA328P based system with soil moisture sensor. Transmitting data on Adafruit Server using Wi-Fi	Controlling the actions of motor pump (ON/OFF) based on the predefined threshold value	Smart DSS unavailable

Sr. No.	Authors and year of publication	Work	Merits	Demerits
21.	Pernapati K. et al. (2019)	µC ESP8266 Node MCU based system with few sensors utilized MQTT Protocol	Controls the functions of motor pump as per threshold value	Smart DSS unavailable
22.	Kiani F. et al. (2018)	Arduino based system with few sensors	Transmits sensors data on server and monitoring through GUI application	Smart DSS unavailable

Table 2.1: Different methodology comparison of IoT-based smart farming

Many researchers have discovered that using image-based evaluation methods rather than manual ones for crop disease identification can lead to increased accuracy and outstanding results. The models created by Xihai Zhang et al. (2018) for the classification of illnesses in maize crop leaves using GoogLeNet and Cifar10 had high accuracy of 98.9% and 98.8%, correspondingly. However, the work offered by them used data from a different source, and there were only 500 original images. So, they had to increase the dataset using a variety of methods. K. Song et al. (2007) developed a plan using SVM to recognize a number of diseases in the leaves of maize crops. The highest detection accuracy is 89.6%. However, this strategy is used with small samples, and the outcome worsens if no. of samples is increased. Through image processing and PNN, L. Chen and L. Y. Wang (2011) proposed a method for spotting illnesses in maize leaves. This has a maximum accuracy of 90.4%. If the number of training samples in this method rises, both detection accuracy and speed will suffer. In addition, numerous initiatives had been made to combat maize leaf disease (L. F. Xu et al. 2015, N. Wang et al. 2009, Z. Qi et al. 2016). Zymoseptoria tritici-related diseases inflicting sick wheat plants were discovered by E. L. Stewart et al. (2014) using a computerized image assessment technique. This approach allows for the measurement of pycinidia dimensions and thickness in addition to a number of other characteristics and their correlation, providing higher accuracy and precision than could be manually assessed.

For the apple crop, Guan Wang et al. (2017) created a DNN system which is able to identify the crop's health stage with 90% accuracy from photographs of the leaves J. G. A. Barbedo (2014) created an image segmentation method that overcomes human error to determine the degree of sickness for a grey environment. Image recognition was illustrated by Le Hoang Thai et al. (2012). The research's accuracy was good, however, when it comes to complicated picture classification, such as face image classification, the processing time efficiency needs to be improved. Cercospora Leaf Spot (CLS) Rater is a computer vision algorithm that was created by Y. Atoum et al. (2016) and colleagues to precisely specify crop photographs in the real world. Better dependability was attained than with manual ratings. A model for plant identification was established by S. Choi (2015), and S. T. Hang & M. Aono (2016) in plantCLEF2015 and plantCLEF2016, they took home the first prize, respectively.

M. Mehdipour Ghazi et al. (2017) increased validation accuracy by combining the results from GoogleNet and VGGNet. S. Sladojevic et al. (2016) created an online dataset and a model to categories 13 different forms of plant diseases. In order to identify 14 crop species and 26 illnesses from more than 54000 photos of the public dataset Plant Village, S. P. Mohanty et al. (2016) developed a neural network model. (Plant Polyphenols, Prenatal Development and Health Outcomes, Biological Systems, 2014). Nearly all of these image-based evaluation methods for plant diseases show a similar and straightforward pattern of behavior (Gong Cheng et al. (2017), H. Al Hiary et al. (2011), Sabtisudha Panigrahi et al. (2018), Mingyuan Xin and Yong Wang (2019)). The most important stage of image classification may involve choosing an efficient classification method, selecting training samples, extracting image processing characteristics, gathering suitable classification approaches, post-classification processing, and accuracy testing [Sandeep Kumar et al. (2012), Anna Bosch et al. (2007), Md Tohidul (2018)). Sorting of images by way of dissimilar ML methods will facilitate society to recover several significant features. The ability of ML/DL techniques to resolve challenging non-linear difficulties on their own using datasets from various sources is one of its main advantages. Administrative analysis based on data is offered by ML/DL approaches. Additionally, they give, the system's introduction of intelligence a robust and adaptable structure (Hossein et al. (2018), Xiao Boxiang et al. (2014)). Precision agriculture can benefit greatly from the wide-ranging use of ML/DL strategies due to their superior performance. Knowing how to plant fitness, physiology, and nutritional status have changed in particular can help determine the best treatments to use and how severe they should be for a certain agricultural region. Typically, a large farm area is divided into smaller control segments with clearly defined different treatments in order to identify and isolate functionally significant parts. Other applications of deep learning include speech analysis, object exposure, and a number of other fields like robotics and medicine (G. Hinton et al. (2012). D.S. ferreira et. al. (2017) utilized caffe software for soybean species and identify broad leaf and grass weeds with approximate 99% accuracy. Precision and sensitivity are the key parameters of research. Ma Juncheng et al. (2017a, b) have developed an image processing algorithm using a convolutional neural network model for downy mildew disease in cucumber species by considering precision parameters. The symptom image segmentation scheme's overall accuracy of 97.29% was demonstrated by the final results, demonstrating the scheme's ability to produce reliable segmentation in actual field circumstances. The disease recognition system was able to identify cucumber downy mildew and powdery mildew because the method had a final accuracy of 95.7%, 93.1% for downy mildew, as well as 98.4% for powdery mildew, individually. Ma Juncheng et. al. (2018) have applied a few popular ML/DL techniques for different diseases identification like Anthracnose, downy mildew, target leaf spots, and powdery mildew in cucumber species along with three parameters precision, sensitivity, and F1 Score. The accuracy of model is quite excellent. Bai Xuebing et al. (2017) applied Fuzzy C-Means algorithm to identify leaf spots in cucumber species. Results indicate that the segmentation error was only 0.12% on average. The suggested approach offers a reliable and efficient segmentation method for classifying and grading apples in the diagnosis of cucumber disease, and it is easily adaptable to other imaging-based agricultural applications. Wenwen Kong et al (2018). applied the concept of CNN with Hyperspectral Imaging for a disease called, Scleractinia sclerotium identification in Oilseed rape stems. The findings showed that chemometrics and hyperspectral imaging may be effectively used to detect plant diseases. They also suggested the best variable selection, machine learning, and calibration transfer techniques for quick and precise plant disease detection. Yusuke Kawasaki et. al. (2015) has exploited the advanced CNN-based System for Plant Disease Detection called, Zucchini yellow mosaic virus and melon yellow spot virus, in cucumber species. The suggested CNN-based system, which also expands the training dataset by generating more pictures, achieves an average accuracy of 94.9% when categorizing cucumbers into two common illness classes and a non-diseased class using the 4-fold cross-validation technique. Artzai Picon et.al (2018) has established a Deep Residual NN-based algorithm to check diseases like Septoria, tan spot, and rust in wheat. The test results regarding The Area under Curve (AUC), sensitivity, specificity and balanced accuracy (BA), show that the balanced accuracy has improved overall, rising from 0.78 to 0.87 under extensive testing and reaching balanced accuracies of more than 0.96 during a pilot test conducted in Germany. Grinblat GL et. al. (2016) used a deep convolutional neural network (CNN) for the problem of plant identification from leaf vein patterns. The outcomes concerning mean accuracy and standard deviation on classifying plants based on the morphology of their leaf veins are useful not only in and of themselves but also as a starting point for additional study on the application of deep learning in agriculture.

Ferentinos, K.P. et al. (2018) has exploited CNN model for crop disease discovery for 25 crops including tomato and strawberry with Average error and success rate for different 58 disease classes. The outcome attained shows that SVM is the top classifier for leaf's diseases recognition. Jihen Amara et al. (2017), have establish a CNN (LeNet architecture) model for a Banana crops with concerning parameters are accuracy, precision, recall and F1 Score along with different diseases Early scorch, Ashen mold, Cottony mold, Late scorch, and tiny whiteness. With little computing effort, the technique can considerably aid in the accurate diagnosis of leaf diseases. Mohammed Brahimi et al. (2017) have settled a CNN (AlexNet, GoogLeNet) model for Tomatoes by considering the parameters, Accuracy, Precision, Macro Precision, Recall, Macro Recall, F1 Score, and Micro F, for Tomato crops with multiple diseases like Yellow Leaf Curl, Tomato mosaic virus, Target Spot, Spider mites, Septoria spot, Late blight, Leaf Mold, Early blight, Bacterial Spot. Here researchers also suggest the usage of occlusion techniques to localize the disease locations, which would aid in human understanding of the illness. Albert C. Cruz et. al. (2017) has developed a CNN (Modified LeNet) model for Olive Tree with concerning parameters like accuracy, Matthew's Correlation Coefficient (MCC) and F1 Score for Olive Quick Decline Syndrome. The model demonstrates potential for fast and automatic discovery of

OQDS by means of less diagnosis period and cost. Chad DeChant et. al. (2017) has established a system based on CNN (Pipeline) model for Corn species with parameter Accuracy, Prediction, and ROC Curve for the disease Northern leaf blight. The test results of the system attained 96.7% accuracy. Fuentes et al. has developed many CNN models for Tomato crop with parameters like, Interaction-over-Union (IOU) and Average Precision for the diseases like Leaf mold, Gray mold, Plague, Miner, Low temperature, Canker, Powdery mildew, Whitefly, and Nutritional excess. An effective deep-learning-based detector for real-time tomato disease and pest recognition has been proposed by researchers in this work. This methodology offers a workable and useful solution for identifying the type and location of infections in tomato plants, which actually distinguishes it significantly from other methods for identifying plant diseases. Bin Liu et. al (2018) has developed a CNN (AlexNet) model for Apple crop with accuracy and confusion matrix parameter for different diseases like Mosaic, Brown spot, Rust, and Alternaria leaf spot. The experimental findings reveal that the proposed convolutional neural network-based disease identification method achieves a complete accuracy of 97.62% under the hold-out test set, the model parameters are reduced by 51,206,928 in comparison to those in the standard AlexNet model, and the accuracy of the projected model with created pathological pictures improves by 10.83%. Yang Lu. Et. al. (2017 a) has developed a CNN (AlexNet inspired) model for Rice crop with parameters like, Recognition Accuracy in terms of Mean, Max, and Stochastic Pooling for the diseases like, Blast, brown spot, bacterial leaf blight, bakanae disease, false smut, sheath blight, sheath rot, seedling blight, bacterial sheath rot, and bacterial wilt. The accuracy rate of the work is 95% with Missing report rate is 5% and the False report rate is 0%. Oppenheim et al. (2017) developed a CNN (VGG) model for Potato crops by taking into consideration of accuracy with different diseases like Black Scurf, Silver Scurf, Common Scab, Black Dot, and Uninfected tuber. The database of pictures utilized in this study included potatoes in various forms, sizes, and states of disease that were painstakingly collected, categorized, and labeled by specialists. In order to better understand the volume of image data required to use deep learning for such classification tasks, the models were trained over various train-test splits. Out of all these split combinations, the best one is selected and then this model is a/the further tested with different parameter variations. So many different approaches and methods were adopted to classify the diseases in the crop. Table 2.2 shows the list of a few research work on plant diseases identification using different techniques.

Sr. No.	Researcher and publication detail	Approach	Crop	Parameter consideration	Diseases
1.	D.S. Ferreira et al. (2017)	Caffe Software replica of AlexNet Pynovisao	Soybean	Precision and sensitivity	Broadleaf and grass weeds
2.	Ma et al. (2018)	DCNN Math ConvNet AlexNet Support Vector Machines (SVM)	Cucumber	Sensitivity, precision and F1 Score	Anthracnose, downy mildew, target leaf spots, and powdery mildew
3.	Ma et al. (2017a, b)	An image processing method using CNN	Cucumber	Precision	Downy mildew
4.	Bai et al. (2017)	Fuzzy C-Means (FCM) algorithm	Cucumber	Frequency, Propagation, Success Rate, Robustness and Accuracy	Leaf spot
5.	Wenwen Kong et al. (2018)	CNN with Hyperspectral Imaging	Oilseed rape stems	Prediction	Scleractinia sclerotium
6.	Yusuke Kawasaki et al. (2015)	CNN based Plant Disease Detection System	Cucumber	Accuracy, Sensitivity and Specificity	MYSV and ZYMV

Sr. No.	Researcher and publication detail	Approach	Crop	Parameter consideration	Diseases
7.	Artzai Picon et al. (2018)	Deep Residual NN-based algorithm	Wheat	The Area under Curve sensitivity, specificity and balanced accuracy (BA)	Septoria, tan spot and rust
8.	Guillermo L. grinbalt (2016)	CNN based plant identification system	Soybean	Mean accuracy and standard deviation	Leaf vein patterns
9.	Ferentinos (2018)	CNN model for crop disease detection	25 crops including tomato and strawberry	Average error and success rate	58 disease classes
10.	Barbedo (2015)	Automatic detection algorithm using HIS	Wheat	F1 score, probability and error rate	Fusarium head blight
11.	Amara et al. (2017)	CNN (LeNet architecture)	Banana	Accuracy, Precision, Recall and F1 Score	Early scorch, Ashen mold, Cottony mold, Late scorch, and tiny whiteness
12.	Cruz et al. (2017)	CNN (Modified LeNet)	Olive Tree	Accuracy, Matthew's Correlation Coefficient (MCC) and F1 Score	Olive Quick Decline Syndrome

Sr. No.	Researcher and publication detail	Approach	Crop	Parameter consideration	Diseases
13.	Brahimi et al. (2017)	CNN (AlexNet, GoogLeNet)	Tomato	Accuracy, Precision, Macro Precision, Recall, Macro Recall, F1 Score and Micro F	Tomato Yellow Leaf Curl, Tomato mosaic virus, Target Spot, Spider mites, Septoria spot, Late blight, Leaf Mold, Early blight, Bacterial Spot
14.	DeChant et al. (2017)	CNN (Pipeline)	Corn	Accuracy, Prediction and ROC Curve	Northern leaf blight
15.	Fuentes et al. (2018)	CNN (Several)	Tomato	Interaction-over-Union (IOU) and Average Precision	Leaf mold, Gray mold, Plague, Miner, Low temperature, Canker, Powdery mildew, Whitefly
16.	Liu et al. (2018)	CNN (AlexNet)	Apple	Accuracy and Confusion Metrix	Mosaic, Brown spot, Rust, and Alternaria leaf spot
17.	Oppenheim et al. (2017)	CNN (VGG)	Potato	Accuracy	Black Scurf, Silver Scurf, Common Scab, Black Dot.

Sr. No.	Researcher and publication detail	Approach	Crop	Parameter consideration	Diseases
18.	Lu et al. (2017a)	CNN (AlexNet inspired)	Rice	Recognition Accuracy in terms of Mean, Max and Stochastic Pooling	Blast, brown spot, bacterial leaf blight, bakanae disease, false smut, sheath blight, sheath rot, seedling blight, bacterial sheath rot, and bacterial wilt
19.	Xihai Zhang et al. (2018)	GoogLeNet and Cifar10	maize crop	Accuracy	Eight common maize leaf diseases southern leaf blight; brown spot; Curvularia leaf spot; rust; dwarf mosaic; gray leaf spot; round spot; northern leaf blight.
20.	K. Song et al. (2007)	SVM	corn crop	Accuracy	Healthy & infected
21.	L. Chen et al. (2011)	PNN	maize crop	Accuracy	Healthy & infected
22.	Guan Wang et al. (2017)	Deep CNN	Apple crop	Accuracy	healthy, early, middle, end stage

Tbale 2.2 Various research methodologies for crop disease recognition

2.3.2 Soil Moisture Prediction

The most crucial resource for the survival and development of all life on Earth is water. Not only is soil moisture essential for plant progress, but it is also crucial to irrigate a farm using a method that correlates the systems of the soil, plants, and atmosphere. On the other hand, when human activity increases and the expanse of excavation is expressively surpassed, the quality of groundwater resources decreases. The ability of the soil to retain water is decreasing due to the continued decline in groundwater levels, which also causes a drop in the water level on farms. Lack of precipitation, especially in desert areas, causes drought on farms and prevents water from refilling at a specific period, which has a negative effect on agricultural development. The majority of existing methods for predicting soil moisture rely on empirical equations, linear regression, and neural networks to create calculations of models (Jitendra Kumar et al. 2022). The empirical formula model is the first type of model. A linear regression model was created by Shu Sufang et al. (2009) to predict soil moisture. Based on a grey correlation analysis of climatic information, the model in this study is able to show patterns. In comparison to other statistical approaches, linear regression has a high quantity of errors and poor performance when the dataset is unstructured. Therefore, it is exceedingly challenging to make the necessary prognosis. Due to improved forecasting training algorithms provided by neural networks, research scientists have begun to use a different technique. J.W. Hummel et al. (2009) collected soil moisture data using a near-infrared reflection sensor and then used several linear regressions to analyze it, the result was a predicted standard deviation of 5.31%. In addition to several input climatic entities, Hou Xiaoli et al. (2016) used the artificial neural network model to anticipate soil moisture index at various depths. In this case, actual entities provided the best match between the results.

Li Ning et al. (2018) enhanced the neural network optimization method using the foundation of soil moisture data attributes. The BP approach has a sluggish rate of training and is vulnerable to local optima because the network's primary parameters are arbitrarily selected. Ji Ronghua et al. (2017) enhanced neural network activation's functionality. The network was trained using the MLP method, and the conventional activation function was substituted with a novel complex number domain. The prediction truthfulness increased by 9.1% when equated to a conventional back-propagation (BP) neural network, providing an additional exact notional underpinning for forecasting soil moisture. By sidestepping the curse of dimensionality problem in neural networks, M. Kashif Gill et al. (2006) estimated soil moisture with an accuracy increase of 89 percent. In order to discover the large-scale optimal starting parameters before training, the evolutionary technique was used. This considerably accelerates training and increases the model's predictive accuracy. Though, it is challenging to create the best mathematical model for predicting soil moisture because soil moisture is influenced by structural and climatic elements. The scalability, simplicity, and prediction accuracy of traditional neural networks are constrained, and their architectural characteristics and processing techniques are insufficient for handling massive volumes of data. A method for predicting soil moisture, precipitation, and drought is put forth by Chen Xiaofeng et al. (2014) and is based on the multidimensional linear correlation of soil moisture. By analyzing the preliminary moisture proportion, daily precipitation, mean temperature, change in saturation, and multivariate linear relationship of soil moisture, this method predicts drought for the following few days.

Jackson et al. (2009) developed a model, which offers advice for drought-resistant irrigation systems, and uses an empirical approach and a time domain reflectometry device (TDR) to estimate the soil moisture flux. The procedure is simpler even if the results are the same. Even though the empirical technique is modest and basic, the model parameters must be recalculated while being transplanted to other areas, which is both slow as well as incompetent. Quick advancement in the field of software has led to the emergence of numerous prediction models. Deep Learning (DL), which Hinton et al. (2006) have developed, makes use of several hidden layers to enhance the ability to classify and fit massive volumes of data with various attributes.

Yu Cai et. al. (2019) has established a model, based on a deep learning regression network (DNNR) with big data fitting capabilities to build a soil moisture forecast system, using the Beijing area as the research object. Selected meteorological parameters might offer useful weights for moisture estimation by combining information, examining the time series of the predictive variables, and elucidating the connection between features and predictive variables through the Taylor diagram. The DL technique is viable as well as successful for predicting soil moisture, according to test results. Its strong theoretical foundation for water consumption in watering the soil as well as drought regularization can be attributed to its decent data fitting besides simplification capabilities, which is able to enhance, involved features, even guaranteeing great performance for forecasting soil moisture content. The MAE and

MSE of the DNNR model are 0.66 & 0.93 respectively. while the corresponding RMSE and R2 Score of the model is0.96 and 0.97 respectively. Calla et al. (2013) used the MLR method to predict Soil Moisture and Ocean Salinity (SMOS) data with covariate data are Land surface temperature (LST) and NDVI from Moderate Resolution Imaging Spectroradiometer (MODIS). In the validation, it was found that for 60% of all datasets, the difference between downscaled soil moisture (%) and ground truth soil moisture (%) was less than 4.1 2%, and for 90% of all datasets, the difference was less than 11%. Srivastava et al. (2013) have utilized land surface temperature (LST) from MODIS as supporting data to predict SMOS with different machine-learning techniques like MLR, SVM, RVM, and ANN. The R2 Score and RMSE value for both techniques, MLR and SVM are same that is 0.698 and 0.013. For the RVM technique R2 Score and RMSE are 0.691 and 0.013 respectively. While for ANN both R2 Score and RMSE are 0.751 and 0.011 respectively. Sa´nchez-Ruiz et al. (2014) utilized the MLR technique to predict SMOS with NDVI and Normalized Difference Water Index from MODIS as covariate data. In this research, the value of the correlation co-efficient is between 0.61 to 0.72. while the centered Root Mean Square Difference is 0.04 m^3/m^3. Im et al. (2016) have used Advanced Microwave Scanning Radiometer for predicting AMSR-E by exploiting many techniques like Random forest (RF), Boosted regression trees (BRT), and cubist. There are many covariate variables like LST, NDVI, Enhanced Vegetation Index, Leaf Area Index, albedo, and evapotranspiration from MODIS. The outcomes of the work show excellent results with a correlation coefficient is between 0. 71 to 0. 84 while it is between 0. 75 to 0.77 and between 0.61 to 0.70 for BRT and cubist techniques respectively. The RMSE is between 0.049–0.057 for RF. While some parameter is between 0. 052 to 0. 078 and between 0. 051 to 0.063 for BRT and cubist techniques respectively. Liu et al. (2018) predict moisture for European Space Agency Climate Change Initiative (ESA CCA) with different techniques like CART (classification and regression tree), KNN, Bayesian and RF. There are numerous covariate variables like LST, NDVI, DEM, and reflectance in red, blue, NIR, and MIR bands. The main performance index is RMSE which is 0.73, 0.74, 0.75, 0.76 for RF, KNN, Bayesian, and CART respectively. Bai et al. (2019) has Used an approach, based on the random forest (RF) model, it is suggested to combine optical/infrared data with synthetic aperture radar (SAR) data to produce downscaled soil moisture active passive (SMAP) soil moisture (SM) data. The approach makes use of the triangle/trapezium feature space between vegetative indexes (VIs), land surface temperature (LST), and

SM as well as active microwaves' sensitivity to surface SM. The performance parameter of the suggested research is RMSE which came between 0.55 to 0.86, and correlation coefficient which came between 0.013 to 0.025. Guevara & Vargas (2019) have established a model using KNN method, to forecast soil moisture spatial patterns (and related uncertainty) over larger geographic areas with higher spatial resolution. This method relies on topography factors generated from geomorphometry and machine learning algorithms to increase the statistical precision and the spatial resolution of satellite soil moisture data over the conterminous United States on a yearly basis (from 27km to 1km grids) (1991-2016). From a digital elevation model, 15 primary and secondary terrain parameters were retrieved. The test results show that RMSE of the suggested research is 0.057 m^3/m^3. Di Long et al. (2019) has developed a novel approach for Surface soil moisture (SSM). The scholars have first, downscaled land surface temperature (LST) output from the China Meteorological Administration Land Data Assimilation System (CLDAS, 0.0625° 0.0625°) using a data fusion approach and MODIS LST acquired on clear-sky days to generate spatially complete and temporally continuous LST maps across the North China Plain. This improved the spatiotemporal completeness of SSM estimates. Second, spatially complete and regular constant 1 km × 1 km SSM was generated based on random forest models combined with quality LST maps, normalized difference vegetation index (NDVI), surface albedo, precipitation, soil texture, SSM background fields from the European Space Agency Soil Moisture Climate Change Initiative (CCI, 0.25° × 0.25°) and CLDAS land surface model (LSM) SSM output (0.0625° × 0.0625°) to be downscaled, and in situ SSM measurements. Third, the importance of different input variables to the downscaled SSM was quantified. Compared with the original CCI and CLDAS SSM, both the accuracy and spatial resolution of the downscaled SSM were largely improved, in terms of a bias (root mean square error) of −0.001 cm^3 /cm^3 (0.041 cm^3 /cm^3) and a correlation coefficient of 0.72. These results are generally comparable and even better than those in published studies, with our SSM maps featuring spatiotemporal completeness and relatively high spatial resolution. Zappa et al. (2019) has predicted moisture for advanced scatterometer (ASCAT) and soil moisture active passive (SMAP) with different covariate parameter alike, Soil texture, topography, and a/the fraction of absorbed green radiation, using the RF technique. In which the outcome of correlation coefficient r is between 0.68 to 0.76, and cRMSD is between 0.054 to 0.061 m^3/m^3. Table 2.3 enlist some research related to moisture prediction

Sr. No.	Authors and year of publication	Soil Moisture data	Covariate data	Types of ML/DL techniques	Diseases/infection
1.	Calla et al. (2013)	SMOS	Land surface temperature (LST) and NDVI from MODIS	MLR	Difference is < 4.12 % for 60% and approximately 11 % for 90% of total datasets
2.	Srivastava et al. (2013)	SMOS	LST from MODIS	MLR	R2 =0.698, RMSE = 0.013
				SVM	R2 = 0.698, RMSE =0.013
				RVM	R2 = 0.691, RMSE = 0.013
				ANN	R2 ¼ 0.751, RMSE ¼ 0.011
3.	Sa´nchez Ruiz et al. (2014)	SMOS	NDVI and Normalized Difference Water Index from MODIS	MLR	Correlation coefficient (r) ¼ 0.61–0.72, cRMSD ¼ 0.04 m^3/m^3
4.	Guevara & Vargas (2019)	ESA CCI	Primary and secondary terrain parameters from DEM	KNN	RMSE = 0.057 m^3/m^3

Sr. No.	Authors and year of publication	Soil Moisture data	Covariate data	Types of ML/DL techniques	Diseases/infection
5.	Im et al. (2016)	AMSR-E	LST, NDVI, Enhanced Vegetation Index, Leaf Area Index, albedo and evapotranspiration from MODIS	RF	r = 0.71–0.84, RMSE = 0.049–0.057
				Boosted regression trees	r = 0.75–0.77, RMSE= 0.052–0.078
				Cubist	r = 0.61–0.70, RMSE = 0.051–0.063
6.	Liu et al. (2018)	ESA CCI	LST, NDVI, DEM, reflectance in red, blue, NIR, and MIR band	CART	RMSE = 0.76
				KNN	RMSE = 0.74
				Bayesian	RMSE = 0.75
				RF	RMSE = 0.73
7.	Bai et al. (2019)	SMAP	SAR data from Sentinel-1, vegetation indices, and LST from MODIS	RF	r = 0.55–0.86, RMSE = 0.013–0.025
8.	Long et al. (2019)	ESA CCI	NDVI, albedo, LST, soil texture, and precipitation	RF	r = 0.72, RMSE = 0.041

Sr. No.	Authors and year of publication	Soil Moisture data	Covariate data	Types of ML/DL techniques	Diseases/infection
9.	Zappa et al. (2019)	ASCAT, SMAP	Soil texture, topography, and fraction of absorbed green radiation	RF	r = 0.68–0.76, cRMSD = 0.054–0.061 m3/m3
10.	Hummel et al. (2001)	Soil Moisture	Soil core samples and NIR sensors	MLR	Standard daviation = 5.31%
11.	Hongli Jiang et al. (2004)	Soil Moisture	IR skin temperature (Ts), NDVI (N*), and prior 30 days accumulated precipitation as the input variables.	ANN	correlation coefficient = 0.9978
12.	Caojun Huang et al. (2011)	Soil Moisture	temperature, rainfall, evaporation, relative humidity sunshine hours other weather factors	Genetic Algorithm BP Neural Network	MAE = 1.92%

Sr. No.	Authors and year of publication	Soil Moisture data	Covariate data	Types of ML/DL techniques	Diseases/infection
13.	Ji Ronghu et al.	Soil Moisture	Rainfall, wind speed and temperature	MLMVN combined with PCA	Accuracy = 0.92
14.	M. Kashif Gill, et al. (2006)	Soil Moisture	Metrological data	SVM, ANN	For SVM Accuracy = 89%, RMSE= 4.05 MSE=3.65 For ANN Accuracy = 74% RMSE = 6.01 MSE = 4.96
15.	C.S. Hajjar et al.	vineyard soils moistures	Pixels coded with RGB color model extracted from soil digital images	MLP, SVR	Correlation coefficient = 0.707 to 0.909

Table 2.3 Several research methodologies for soil moisture prediction

2.4 RESEARCH GAPS

On ICT-based PA approaches, numerous study articles have been reported to date in a variety of research journals. Only some methods of soil parameter sensing schemes, Decision Support Systems (DSS) for Precision Agriculture (PA) mechanisms, smart irrigation, and fertilizer applications are the subject of some research. However, information and communication technology (ICT) is used less in Precision Agriculture (PA) processes that are run by clever DSS models. ICT systems and DSS for PA mechanisms are developing less rapidly. A low-cost and flexible image-processing method for PA mechanisms is also still in the research stage at numerous universities and research institutions. Similarly, to this, there is still no study being done on early predictions of current soil moisture content. The majority of PA-related projects use sophisticated irrigation methods and decision-support system-based farm management tools (DSS).

There are currently no complete and sufficient ICT integrated Decision Support System (DSS) tools that can help PA professionals transform the vast amount of data collected into useful decision-making. In the early years of PA, in 1994, the need for a software package to encourage farmers when they draw findings using PA was raised (S. Blackmoreet al, 1994). The majority of PA computer software programmers only handle data in user-friendly formats and manage data transformation.

2.5 ENCAPSULATION

The utilization of PA technology has supposedly improved during the last 20 years, contrary to popular assumption. However, the number of farmer suicides that have occurred in several Indian countries over the past few decades indicates that Indian farmers are still a long way from using PA technology and its applications in the agricultural sector.

This assessment summarizes the applicability and most recent developments in Precision Agriculture (PA) mechanisms based on Information and Communication Technology (ICT). Modern sensing technologies are additionally crucial for the development of ICT-based applications. As a result, numerous studies on the creation of soil parameter sensing systems and the application of these sensors in ICT-based agriculture systems have been published to date.

According to the survey, very few studies on the methodology for compact lab-on-a-chip soil parameter sensing have been conducted. The sole published measurement of soil moisture utilizing lab-on-a-chip has the highest accuracy to date. Precision agriculture can be implemented by measuring additional soil properties with greater accuracy using a similar lab-on-a-chip technique. The review also shows that practically all required soil characteristics can be analyzed using soil parameter sensing, however, sensor configurations can affect measurement accuracy. The use of various sensor system technologies with soil parameter sensing methodology would have a substantial influence on the productivity of the land. ICT-based agriculture also encompasses a wide range of instruments, methods, and approaches. It is necessary to gain access to the use of new ICT-based approaches, like the system of devices to transfer the data without the involvement of humans, in order to make it more efficient, increase productivity, be competent to international markets, and reduce the cost and time of human intervention. The adoption of smart farming, which is critical in the field of agriculture with the intention of transitioning from traditional to sustainable agricultural methods, can therefore be integrated with internet-based approaches to agriculture in order to achieve high production.

ICT-based agriculture also includes a broad range of tools, techniques, and strategies. In order to improve efficiency, productivity, and competence in global markets, and decrease the cost and time of human intervention, access to new ICT-based ways is required. One such approach is the system of devices that transfer data without the involvement of humans. Therefore, internet-based approaches to agriculture can be combined with the adoption of smart farming, which is crucial in the field of agriculture in order to move from conventional to sustainable agricultural practices, in order to achieve high productivity.

Site managers can provide farmers with updates on the condition of the field in real time, evaluate their performance, and share insights and strategies that teams in different fields utilize by using IoT monitoring tools. IoT for precision agriculture enhances planning, risk management, and monitoring of the farm, fields, and animals. It offers a wide choice of less expensive and more ambitious technology and covers almost all dimensions of managing an agricultural operation. Potential Internet of Things use cases may differ depending on the farm's focus. Some of the most common varieties of precision farming systems are as follows.

- **Climate Surveillance**: Farmers may track and forecast weather conditions in a specific area with the aid of weather stations integrated with farming stations. The data is sent to cloud-based storage by linked devices once they have gathered environmental information. Farm managers can then use the data for crop selection and climate mapping.
- **Plant Observation**: Crop management tools are an essential part of effectively utilizing precision agriculture technologies. These gadgets are often installed in the field, where they will keep an eye on crop health, water levels, and other important biochemical and physical characteristics. A farmer may proactively manage anomalies, create prediction-based models

and plans, and stop potentially dangerous illnesses using crop monitoring systems.

- **Cattle Surveillance**: The control of animals requires sensors even more than crop maintenance. One way they can help prevent cattle loss is by acting as location trackers. Additionally, the farm manager will receive real-time information about the health and hunger levels of the cows, pigs, and other farm animals. The most popular type of cattle monitoring equipment is connected collar tags. They don't put the animal through any stress while still giving farmers current information.

In the proposed methodology the concept of IoT and big data applied regarding PA, in terms of crop diseases identification using image processing by neural network approach and soil moisture prediction using different ML and DL techniques. Hence developing an IoT based, intelligent decision feedback system, to check whether the crop is healthy or diseased. Simultaneously the system continuously monitors the moisture and predicts the moisture for smart irrigation. The survey is conducted based on these goals to select the best techniques to get desirable outcomes.