A Comprehensive Literature Study on Precision Agriculture: Tools and Techniques

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Abstract

Due to digitization, data has become a tsunami in almost every data-driven business sector. The information wave has been greatly boosted by man-to-machine (M2M) digital data management. An explosion in the use of ICT for farm management has pushed technical solutions into rural areas and benefited farmers and customers alike. This study discusses the benefits and possible pitfalls of using information and communication technology (ICT) in conventional farming. Information technology (IT), the Internet of Things (IoT), and robotics are discussed, along with the roles of Machine learning (ML), Artificial intelligence (AI), and sensors in farming. Drones are also being studied for crop surveillance and yield optimization management. Global and state-of-the-art Internet of Things (IoT) agricultural platforms are emphasized when relevant. This article analyse the most current publications pertaining to precision agriculture using ML and AI techniques. This study further details about current and future developments in AI and identify existing and prospective research concerns in AI for agriculture based on this thorough extensive literature evaluation.

Keywords
Precision Agriculture, Machine learning, Artificial intelligence, ICT

1. Computer-Aided Automated Agriculture Systems

The significance of agriculture in the international economy is crucial. As the world's population rises, so will the demands placed on farms. Due to its central role in providing for human needs, agriculture is a pressing issue on a global scale. There are still many people going hungry in several parts of the world, especially in Africa [1]. Most poor countries rely heavily on agriculture for their economies. In many nations, agriculture plays a crucial role in the economy. It is not just for the good of the country, but also as a way of life [2]. A large portion of the population relies on agriculture to provide their sustenance. It continued to play an essential role in the development of human civilisation. Plants like sugar cane, rice, and tomatoes are just a few examples of the many crops that fall under the broad umbrella of agriculture, which also encompasses their care, cultivation, monitoring, and harvesting. As industrialization has advanced in recent decades, agriculture has adapted to take advantage of the ensuing commercial climate.

High agricultural yields are largely attributable to the widespread use of soil monitoring and water saving practices. Agriculturalists devised the concept of precision agriculture [3] by factoring in the accessibility of soil, water, and favourable field conditions. New scientific areas, such as agriculture and precision agriculture (sometimes known as "virtual agriculture"), have evolved to use data-intensive approaches to increase agricultural output while reducing environmental damage [4, 5]. To increase yields, farmers are increasingly adopting the practice of precision agriculture [5]. It's a way to manage a farm that involves keeping an eye on things, making some educated guesses, and acting accordingly when yield metrics change. Based on the data shown in [5], India is only responsible for 2.59 percent of global organic output despite having 57.8 million hectares of total agriculture land. This is because both a lack of education about precision farming and the use of inefficient farming methods contribute to this problem. Efficient agriculture may be improved by the combined use of precision farming technology based on the Internet of Things (IoT) and the Machine Learning (ML) methodology [6]. More informed, timely choices may be made to boost yields with the use of diverse data sets used in precision agriculture [3]. To better comprehend the operating environment (the interplay of dynamic crop, soil, and weather variables) and the operation itself (machine data), a variety of sensors offer the data needed for more precise and rapid decision making [6]. [7] Communications technology and AI paradigms may be used to transmit and evaluate this data. Now more than ever, Precision Agriculture encompasses every facet of crop production. Since Precision Agriculture is an information and computing-intensive technology, its success relies heavily on efficient and trustworthy techniques for gathering and analysing data from particular locations [8].

Creating intelligent systems to aid farmers in both new and current farms is a priority. Using IoT

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principles, [7] investigates a variety of industrial agricultural facilities in tandem with farmers and producers to design unique features. They leverage the Internet of Things' architecture, operational regulations, and more efficient operations inside a decentralized framework based on the concepts of edge and fog computing. In the course of our research, we have come across a number of articles that explore the usage of IoT in precision agriculture. Automatic and Unmonitored Smart Irrigation System was presented by [1-3, 5, 7, 9-14] as an extension of Internet of Things (IoT) approaches. They also examined the hardware implementation to ensure the accuracy of the ML methods and the improved formulae [2].

The photos collected by the IoT-based multimedia sensor go through a series of processing steps, including the use of one of the Machine Learning algorithms, Deep Learning. This suggested framework is trained in real-time using a combination of digital imaging methods for pictures provided by multimedia sensors and machine learning algorithms. According to [5], a precision agricultural monitoring strategy that makes use of satellite data (Landsat 8) is feasible. The suggested method is rigorously evaluated and verified using a wide range of geographical and temporal outcomes obtained from Landsat 8. The ability to tackle big nonlinear problems autonomously using data sets from many sources is a major advantage of the Machine Learning (ML) approach. Sensors may collect data with the use of ML methods such as convolution neural networks (CNNs), artificial neural networks (ANNs), Random forest (RF), regression trees, etc. Additionally, ML enables improved decision-making in real-time circumstances with little to no human intervention. Precision agriculture may benefit greatly from the use of ML approaches because of their broad applicability [6].

1.1. Precision Agriculture System in India

In a third world nation like India, agriculture is the major source of income. Most farmers are either very tiny or very marginal operations, with just a few scattered plots of land between them. Access to abundant sun energy, one of the most essential natural resources, increases agricultural production. Crops are adapted in various parts of India based on factors such as soil type and climate. Across India, the vast majority of farmers have followed the same crop rotation for decades. Soil and environmental factors are constantly shifting as a result of human interventions and artificial eutrophication in natural sources. A major challenge to India's food and environmental security is land degradation, as stated in FAO's "The India national programming framework, 2016-17" [1].

Farmers are unwavering in their adherence to established agricultural rotations, notwithstanding the current situation. The present need is to adapt the crop pattern and cropping style to the circumstances, so as to meet the changing parameters. The ALSE (Agriculture Land Suitability Evaluator) is an example of a current advice system [2]. The original data mining strategy was used to identify and map the cropped land in West Africa based on coarse-resolution images, and the results were compared to those obtained using the standard ISODATA method [3], which operates at the northern edge of the sub-Saharan Africa area. The availability of farmable land in the agricultural regency of Tuban on Java Island was evaluated [4]. It is based on spatial multi-criteria analysis, which takes into account factors including soil type, land capacity, elevation, slope, slope direction, land use/land cover, accessibility, and climate. North Carolina conducted a wheat crop suitability study, and a similar study was conducted for the area for the crop soybeans. Further in [5] traceable food-safety with Blockchain Technology & Smart Contracts is developed which would make it transparent and tamper-proof. None of the aforementioned automated technologies, despite their widespread usage across nations and vast arable swaths, are suitable for the marginal or tiny fragmented fields typical of highly specialized farming. Farmers in developing nations like India, concerned about their increasing reliance on the natural environment for crop production due to the increasing fragmentation of their cropping regions, pose a number of issues, included as shown in table 1.

Table 1: Farming Issues – Scope for Precision agriculture

How can we keep track of the values of the variables that affect crop output right now?
Which crop would be most suited to sustain with dynamic changes in climatic conditions?
How to Maintain Soil Quality and Produce Desired Yield?

Agricultural universities in India study and investigate all of these concerns on a constant basis, and they disseminate their findings via publications, exhibits, and other means of public dissemination. In addition, each Taluka has a Krishi Vigyan Kendra (a farmers' resource center) where farmers may bring soil and water samples to be tested, learn their current parameter values, and get crop-specific recommendations. Environmental parameter values are not included in this report. Although most farmers would benefit from annual trips to the Krishi Vigyan Kendra to have their soil and water tested and get agricultural advice, few actually make the effort to do so. They haven't stopped their routine adjustments to the crop pattern or their fertilizer applications.

The available static systems and reports are difficult to use, thus farmers do not reap its benefits. The suggested system consists of two components: an Agriculture Field Monitoring Model (AMM) that keeps tabs on the state of the soil and the environment, and an Agriculture Advisory System (AAS) that provides advice based on a hybrid machine learning/human model of decision making. The supervised nature of this hybrid strategy makes it ideal for the agriculture dataset.

As a supervised machine learning approach, classification attempts to determine what category a new instance will fall into. Here, we categorize the viability of a certain crop in light of the soil and environmental factors at our disposal. ID3 is a classification model that uses a decision tree, although it can only be used with discrete characteristics and not continuous ones. This data collection is thus inadequate for agricultural use. A binary decision tree, the CART method may sort the input cases into two categories. There are five possible values for crop suitability, which are denoted by the letters S1, S2, S3, N1, and N2. All currently available classification algorithms take all attributes into account throughout the training process. Nevertheless, there are just a handful of factors that change significantly from one crop phase to the next in the agricultural dataset (three stages of crop seeding, germination, and maturity). As a result, we need to tailor a machine learning approach to the specific demands of the agricultural dataset.

Previous literature reviews often use cloud computing and IoT. For the most part, cloud computing and the IoT are being used together in the previously published review studies. Our desire to fill this gap in the literature is what drove us to write this article, which contrasts with the minority of SLRs that use ML methods to study the IoT. More specifically, we used AI methods to run an SLR on the Internet of Things from January 2013 to June 2022. Specifically, this SLR aims to (1) research the application of AI techniques for IoT-based prediction in precision agriculture, (2) examine the use of AI techniques for IoT-based prediction in different crop kinds, and (3) explore other domains where AI techniques have been used for prediction. In order to guarantee the authenticity and quality of the chosen literature, the review uses a systematic review technique to search for and choose research from reputable sources. In addition, this study offers an in-depth evaluation of IoT-based AI algorithms for application in precision agriculture, focusing on their performance on a variety of datasets. This analysis concludes with a few suggestions for future academics interested in combining IoT and AI in the context of precision agriculture.

2. Rationale of the study

Cloud computing and the Internet of Things have been widely used in previous literature evaluations. Previous literature reviews have generally shown that cloud computing and the Internet of Things are utilized in tandem. As there are only a few number of SLRs that make use of ML techniques to investigate the IoT, we felt compelled to produce this article in order to address this void in the literature. With the use of AI techniques, we conducted an SLR on the IoT from January 2013 to June 2022. This SLR seeks to investigate the following areas of interest: (1) the use of AI methods for IoT-based prediction in precision agriculture; (2) the use of AI/ML based Image processing methods for disease prediction various types of crops; and (3) the use of AI techniques for prediction in other contexts pertaining to precision agriculture. The review employs a systematic review approach to seek for and choose research from reliable sources, guaranteeing the authenticity and quality of the selected literature. Further, the report provides a comprehensive analysis of various computational intelligence algorithms using in the context of precision agriculture, with an emphasis on their effectiveness across different datasets. At the end of this evaluation, several recommendations are made for future researchers interested in precision agriculture.

3. Review and Discussion on Precision Agriculture

Based on the preliminary study of the selected research articles, it is observed that although much research has been conducted on some aspects of precision agriculture, much more study is required. Table 3 displays some of the precision agriculture variables we discovered, including: pest detection, weed detection, soil monitoring, fruit detection, plant monitoring, plant growth, water level monitoring, irrigation, humidity, weather forecasting, temperature, crop yield forecasting, crop production, crop monitoring, crop growth, crop forecasting, and crop classification. Irrigation, soil monitoring, temperature, and humidity have all received a lot of study. There is a varied need to investigate additional essential factors in precision agriculture, but these have received the most attention in the literature.

The soil is a complex natural resource with many different processes and mechanisms. To learn more about soil characteristics, dynamic ecosystems have been created. Temperature of the soil is vital for proper soil analysis since climatic change impacts the area and eco-environmental state. In order to get reliable estimates of soil quality without spending a lot of time or money, computer analysis based on ML approaches may be used. Automated irrigation and crop yield monitoring utilizing

IoT and ML have been created for the agricultural sector [15]. As another example Soil moisture levels were determined by implementing a deep learning algorithm into an Agricultural Monitoring System [16]. When done properly, agricultural water management contributes significantly to hydrological, climatological, and agronomic equilibrium.

To effectively manage resources during crop production, reliable evapotranspiration measurements are crucial in the planning, construction, and operation of irrigation systems. The IoT-based WSN Water Monitoring System uses cloud-based monitoring as a service, machine learning, and IoT to keep tabs on the state of the world's water supplies [17]. Among the most important aspects of agriculture is the ability to accurately estimate crops and harvest yields, and precision agriculture is a major part of this field. One of the primary goals of precision agriculture is to maximize output by means of yield mapping, yield estimate, and other forms of crop management. In order to increase output in precision agriculture, machine learning and other AI methods have been used. As a means of increasing crop cultivation using neural networks in AI [19], a method for predicting cotton lint output using crop indices phenology was devised [18] that increases crop prediction in agriculture with the use of an IoT system built on deep reinforcement learning [20]. It is observed from the literature study that major verticals in precision agriculture are Soil analysis and Plant disease detection.

Table 3: Major verticals focused for research in precision agriculture

Author	Vertical	Area	Contribution
A. Chlingaryan et.al[21] 2018	Crop	Crop Yield prediction	Machine learning approaches for crop yield prediction
C. Sun et.al[22] 2019		Crop Type Classification	Improving Crop-Type Mapping in the Subtropical Agriculture Region
C. Yang et.al[23] 2013		Crop growth	Assess Crop Growth and Yield Variability
F. Tseng et.al[24] 2019		Crop Selection	Intelligent Agriculture-Based Crop Selection Analysis
D. Murugan et.al[25] 2017	Weather	Weather prediction	Adaptive Approach for Precision Agriculture Monitoring with Drone and Satellite Data
Kingsley Eghonghon Ukhurebor et.al[26] 2022		Weather forecasting	Weather forecasting for future farming
Bagha, H et.al[27] 2022		Temperature and Humidity	Hybrid sensing platform for precision agriculture
Victor Grimblatt et al. (2019)[29]	Soil	Soil fertility	To improve soil yield
Bhanu K N et al. (2020) [28]		Soil classification	Identification of soil suitability for agriculture
Y. Ampatzidis et.al 2019 [30]	Plant	Plant Growth	Rootstock evaluation utilizing UAV-based remote sensing and artificial intelligence,
A. Catini et.al 2019[31]		Plant Monitoring	Sensor Node configuration for Remote Monitoring of Plants

3.1 Studies on Soil Analysis

China published research on a 3-class system for describing soil types in 2018. To conduct their study, W. Wu et al. [32] gathered dirt from southwestern China. The pipette technique and the USDA triangle are used to correctly categorize 43 soil samples. In their analysis, they looked at the differences between the Support Vector Machine (SVM), the Artificial Neural Network (ANN), and the Decision Tree (DT). For clay, loam, and sand, the reported accuracy values were 79.4%, 99.2%, and 66.1%, respectively.

In 2018, Ethiopian researchers Mengistu and Alemayehu [33] reported utilizing a hybrid method for analyzing soil texture. After training a model using the Back Propagation Neural Network (BPNN) technique, they found that it could correctly categorize 6 distinct soil textures 89.7 percent of the time. They took soil pictures and used feature extraction to determine 7 distinct soil texture characteristics to feed into a BPNN. Their analysis relied on the categorization of 540 photos. To train the model, they utilized 70% of the soil photos and to test it, they used 30%.

Irena et al. [34] presented an image processing strategy for investigating soil deterioration in 2017. Single Lens Reflex (SLR) cameras were used to take pictures of the soil as they dissected five types of soil, from sandy loam to loam to silty loam, etc. Daily, the authors retrieved color and texture data from soil photos using shadow ratio, gradual change, and the Huang thresholding approach to track soil deterioration.

By comparing extracted characteristics for similarity, Honawad et al. [35] explored the soil categorization method in 2017. Using a Sony digital camera, they snapped a hundred pictures of dirt in various settings. The research group showcased a retrieval technique for soil photos that relied on the images' textural characteristics.

Srunitha.k and S.Padmavathi [36] published findings on the efficacy of the SVM classifier for identifying soil textures in 2016. They took 175 samples of different types of soil, such as sand, silt, peat, and more. As an image retrieval system, their model matched a query picture to the training image. After processing the soil pictures with a Gabor and low mask filter, they calculated the average histogram. They reported an accuracy of 90.7% when classifying three kinds of soil texture but only 74.4% while classifying seven types of soil texture.

Partial Least Squares Discriminant Analysis (PLS-DA) and the multinomial support vector machine (SVM) were used by Guang Q et al. [37] of China to categorize 7 distinct soil textures in 2015. For 7 unique soil types, they found that multiSVM had an accuracy of 96.67 percent while PLS-DA had an accuracy of 93.33 percent.

Vibhute et al. [38] used the SVM classifier's Radial Base (RB) kernel to categorize hyperspectral remote sensing soil data into five distinct categories of soil in 2015. The model has an overall Kappa of 0.57, indicating an accuracy of 71.18%. They discovered that, owing to the complexity of hyperspectral soil pictures, SVM is not a useful supervised classification technique for soil classification. In their study, they distinguished between sandy, black sandy, black clay, red sandy, and gray clay soil.

3.2 Studies on Plant disease detection and Classification

In 2018, Fuentes et al. [39] used CNN to report on a segmentation-based plant disease detection system. The photos were obtained from the publicly available dataset at plant village, then segmentation based on the correlation coefficient and the harmonic mean was used to isolate the affected area. More than 90% accuracy was achieved in disease classification by using VGGNet and AlexNet to extract deep features from the plant village picture dataset, followed by Multi SVM.

In 2018, Ma et al. [40] presented the results of another Chinese research on utilizing CNN to identify diseases in cucumbers. They categorized four distinct cucumber illnesses. Some of the pictures originated from the plant village dataset, while others were taken using a digital camera. According to a research, 14,208 cucumber pictures were created using an enhancement approach. AlexNet CNN classification was found to have an accuracy of 92.6% by the authors.

Palestinian researchers B. A. Ashqar and S. S. Abu-Naser published their findings on tomato leaves in 2018. A total of 9000 photos, both healthy and sick, of tomatoes were used in the experiment. Images of tomato leaves were fed into a CNN model, and it achieved an accuracy of 99.84% in the color domain and 95.54% in the gray domain. Reporting the transfer learning of CNN for plant disease detection, a paper was published in Greece.by K. P [41].

Ferentinos in 2018 [42]. The author's program employed AlexNet, GoogleNet, and VGGNet on 87,848 photos from 58 distinct disease classifications in addition to the healthy ones. They sorted things in a lab and out in the field. VGGNet achieved a maximum accuracy of 99.48% with an average error of 0.0223 throughout the course of 48 iterations.

Researchers J. Amara et al. [43] from Tunisia studied the use of deep learning to identify banana leaf diseases in 2017. Banana leaf illnesses were categorized using convolutional neural network (LeNet) transfer learning methods. They used a digital camera to take pictures of both diseased and healthy banana leaves, and the resulting dataset has over 3,700 photos. They performed their tests in both the color and grayscale domains of the banana picture. In preparation for the test, the picture was resized to 60x60. They were successful with a 99% success rate in the color domain and a 97% success rate in the gray domain. Cassava disease detection in the United States was the subject of a research published in 2017 by A. Ramcharan et al. [44]. With the use of a Sony digital camera, they were able to snap 11,670 photos of cassava. Their 93% accuracy was attained using GoogleNet (Inception V3) in their trial.

New guidelines for categorizing potato diseases were proposed in 2017 by D. Oppenheim and G. Shani [45]. A smartphone camera was used to take 400 pictures of potatoes. There were a total of 10 layers in the CNN they used for their research: 5 convolution layers, 5 max-pooling layers, and 3 fully linked layers. They put the model through its paces using a variety of training and testing sets of photos, reporting a best-case scenario of 95.85% accuracy using a 90% training set and a 10% test set.

In 2016, scientists from Serbia and Italy collaborated on a study aimed at better categorizing and identifying plant diseases. Photos of the various

plants were gathered from the internet and submitted by S. Sladojevic et al. [46]. They conducted their research using a dataset including 33,469 photos (After augmentation). In the experiment, they used CaffeNet, a CNN model trained in the GPU setting, and attained an overall accuracy of 96.3%.

CNN (AlexNet and GoogleNet) were used to categorize 26 plant diseases in 2016, as reported by Mohanty et al. [47]. Tests were conducted in the color, grayscale, and segmented color domains. All of the plant photos (plant village dataset) were separated into training and testing sets. They found that an average of 99.35% was achieved in their research.

Table 6: Glimpse of ICT implementations for Precision Agriculture

Author	Objective	Development Platform	Sensors Utilised
Bhanu, K. N. et.al [48]	Smart Irrigation system	Arduino UNO	• Water proof Sensor • Soil Water Content • Temperature • Humidity
Laksiri, H. G. et.al [49]	Optimized Irrigation system for Srilanka farming conditions	NodeMCU	• Soil Water Content • Temperature • Humidity
Saraf. et.al [50]	Agriculture Monitoring and Controlling System	AtMega 328 microcontroller	• Ambient temperature and humidity sensor • Water level Sensor • Zigbee Transceiver
Wiangtong. Et.al[51]	Versatile platform for precision farming	Arduino Mega2560 Hysteresis control	• Loop time control • specific time control • conditional control • temperature and humidity hysteresis control
Marcu. et.al [52]	System for smart agriculture	Libelium Platform	• Contactless sensor for measuring surface temperature • UV global radiation sensor • sensor for leaf, flower bud temperature measurement • Shortwave global radiation sensor • Humidity and pressure sensor
Dolci, Rob.et.al [53]	Precision farming and food manufacturing	Bayesian network analysis, multi-variate analysis	• Temperature • pH • CO2 • Humidity

4. Open Challenges

4.1 Challenges in IoT deployment for Precision Agriculture

Most IoT applications provide their own means of identifying research and development difficulties and creating a roadmap for future research operations to achieve a trustworthy and practically applicable solution. Correct identification of research priorities was the foundation for developing the roadmap, which was based on assessments of the following indicators

A thorough familiarity with IoT framework is required. The largest obstacle in SOA is the need for providers and requesters to interact effectively with each other despite their differences. In other words, the right technology must be found to set up the interface for communication. The primary difficulty is associating a globally or locally unique identifier with an entity in a way that allows for unambiguous identification and retrieval.

When objects are synchronized via the Internet with the assistance of communication devices, there is a massive creation of data that requires accurate identification of incoming data and subsequent signal processing. Therefore, the following issues are crucially important: semantic interoperability, accurate service discovery, service composition, data exchange and cooperation, correct identification of autonomous agents. Standards should be developed to accommodate a broad variety of applications and fulfill common needs of all the conceivable applications connected to IoT

4.2 Challenges in Plant disease detection

In addition to the issues that have been brought up so far, there are several more that have an impact on automatically diagnosing diseases. As a first, we have true real-time functionality. While it is assumed that the offered techniques would run on time, only a subset of applications truly need running in realtime. As more and more processing power becomes accessible, it should become simpler to satisfy real-time needs. However, as picture resolution improves, more processing power is required. In addition, the resources of mobile gadgets and inexpensive computers like the Raspberry Pi (Raspberry Pi Foundation, Cambridgeshire, UK) are restricted. Therefore, depending on the context, it may be crucial to minimize the amount of processing power and storage space needed. Many methods have been developed to lessen the burden on computers, including the use of more efficient programming languages, the organization of code to lessen the load on computers, and the downscaling of images during processing.

Another typical issue is covariate shift, which occurs when there are discrepancies between the distributions of the training data used to develop the model and the distributions of the data on which the model is to be applied. Particularly pertinent to the topic at hand, automated plant disease detection, since symptom features may change with location.

5. Future Scope

Rapid use of digital image processing is being driven by the need to mimic human visual skills as a first stage in the process of automating agricultural tasks. One of the most difficult problems in progress is the development of a computer vision system for pant disease detection and severity evaluation. We set out to address some of the key issues that need to be fixed before a practical image-based diagnostic system can be made widely accessible, and that's what this article is all about. Restricting the range of feasible capture conditions is one approach to overcoming the current technological restrictions that influence this field. Unfortunately, this tactic has the unintended consequence of discouraging many would-be users from embracing the technology due to the extra work necessary to fulfill those limits. Many difficulties will persist even under severe limitations. Advanced methods from computer vision and machine learning, such as Markov Random Fields (Li, 2009), Graph Theory (Bondy & Murthy, 2008), Deep Learning (Deng and Yu, 2014), Mean Shift (Cheng, 1995), and Large Margin Nearest Neighbor (LMNN) classification (Weinberger, Blitzer, & Saul, 2009), could help alleviate some of the main challenges.

In particular, LMNN has the ability to reduce the negative effects of low within-class variance and significant intra-class variation. While a lack of interest is unlikely to account for the underutilization of resources and the relatively low levels of engagement seen in the image processing and machine learning fields, this may be the case. Most likely, this is due to a lack of sufficient picture databases on which to conduct the study. Unfortunately, the few current databases are either inadequate or inaccessible to researchers. The good news is that efforts are being made to fix this problem, such as the database created by Hughes and Salathe (2015) (https://www.plantvillage.org/), which has over 50,000 photos of healthy and sick plants. Since plant pathologists and agricultural engineers frequently need to rely on resources other than their own sight (such as laboratory analysis) to arrive at a reliable diagnosis, there will be many situations that cannot be dealt with by automatic methods based solely on computer vision and image processing techniques, even with the use of more advanced techniques.

6. Conclusion

This article provides a comprehensive analysis of the present state of computational intelligence applications in precision agriculture Furthermore, AI and computer vision have emerged as emerging concepts in agriculture with the intention of enhancing farm management. This article reveals that the vast majority of AI, ML and Internet of Things (IoT) based smart farming technologies that were used to keep track of agricultural data across the many projects it covers. Many of the use cases for the Internet of Things (IoT) that were addressed in this article made use of numerous network protocols at once to achieve optimal performance. The evaluation presented herein showed that the role of IoT in smart farming is becoming more marginal. A farmer will get an all-encompassing assessment of his or her business in terms of crop and animal management, weather and soil quality using precision agriculture techniques In the future, this study might be used as a resource for budding researchers in the area of ICT enabled farming.

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