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TOPICAL REVIEW

Evaluation of Machine Learning Approaches for Precision Farming in Smart Agriculture System: A Comprehensive Review

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ABSTRACT In the era of digital data proliferation, agriculture stands on the cusp of a transformative revolution driven by Machine Learning (ML). This study delves into the intricate interplay between Information and Communications Technology (ICT) and conventional agriculture, emphasizing the role of ML in reshaping farming practices. With the ongoing data tsunami impacting data-driven businesses, the fusion of smart farming and precision agriculture emerges as a beacon of innovation. ML algorithms, analyzing historical and real-time environmental data, soil conditioning, predicts suitable crop for maximum yields, detect diseases, and optimize irrigation in smart farming, facilitating informed decision-making. Precision agriculture benefits from autonomous vehicles and drones, driven by ML, ensuring precision in planting, harvesting, and crop monitoring. Resource efficiency increases as ML optimizes energy consumption, manages fertilizer application, and promotes climate-resilient practices. This comprehensive assessment underscores ML's pivotal role in maximizing productivity, minimizing environmental impact, and navigating the complexities of modern agriculture.

INDEX TERMS Smart agriculture, precision farming, machine learning, unmanned aerial vehicles, artificial intelligence.

I. INTRODUCTION

The 6.4% of global Gross Domestic Product (GDP) comes from agriculture, making it the primary source of both food supply and economic growth. In nine nations throughout the world, agriculture is a major economic driver. Energy and employment for millions of people are provided by the agricultural sector [1]. Supplying the demands of the world's population would need a threefold rise in yearly wheat output and a more than twofold increase in annual meat production by 2050 [2]. Increases in grain production yields will provide a steady supply. It is necessary to adopt a more modern perspective on farming and to expand the scale of your crop production. The question of whether or not this can be accomplished in a way that is both sustainable and welcoming remains open. But re-engineering the agricultural operations at massive size and speed calls for a major and quick transition. Because of climate change and population expansion, the agricultural industry is looking for ways to apply new technologies to increase yields. As Artificial Intelligence (AI) advances, it is being put to more useful use in the agricultural sector. Concurrently, the Fourth Industrial

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Revolution (Industry 4.0) and the Internet of Things (IoTs) make it possible for brand-new technological developments and ground-breaking ideas to emerge. Smart agriculture, commonly known as "Agriculture 4.0," is the use of new technology and methods to farming that improves crop yield while simultaneously lowering resource consumption. Environment-specific monitoring and forecasting tools will make this a reality. With the new tools made available by smart farming, agricultural processes may be improved, leading to higher yields while using less resources. In order to take advantage of new ideas, Smart Farming (SF) employs a wide range of technologies and platforms as shown in Figure 1 [3].

Improvements in productivity, sustainability, equity, and transparency will result from the "digital agricultural revolution" in the agricultural sector. The agriculture industry, however, needs wider use of technology to take full benefit of their improved efficacy. Correct data generation, transport, and processing, as well as protection from assaults, are essential for Agriculture 4.0 [4]. Technologies reliant on data, such as analytics and smart systems, are useless if their integrity isn't managed appropriately. The integrity of the network and all devices linked to it may be compromised if the system fails due to defective hardware or in combination with other assaults. Privacy leaks, broken trust, and missing resources are just some of the security concerns that crop up when resources from different categories are combined.

A. SMART AGRICULTURE AND PRECISION FARMING: A DEFINITION

An approach to agricultural management known as "smart Agriculture (SA)" focuses on equipping agriculture with the means to monitor, automate, and analyze their processes via the use of cutting-edge technology, such as big data, the cloud, and the IoT. Improving agricultural yields and supporting management choices via the use of high-tech sensor and analytic tools is known as Precision Farming (PF). The weather (sun, rain, hail), farm machinery, animals, passers-by, and humans are just some of the environmental factors that farm smart devices must contend with. Because of the aforementioned factors, the sophistication of our farm is open to attacks that have not been seen before. Any of these safeguards will be rendered useless if the sensor is moved or damaged by accident. When these devices aren't physically attached to anything, as is frequently the case with smart cities, external agents may easily find a way around them. There is a clear weakness in agricultural systems due to the absence of protection. ML's potential uses on a grander scale in agriculture are just now being explored. Research and improvement in all areas of agriculture will eventually yield miraculous outcomes. "Agriculture is the cornerstone of civilization and any stable economy," said economist Allan Savory.

Early applications of PF were targeting certain soil conditions with fertilizer applications. Since then, PF has found widespread usage in the development of autonomous farming equipment, farm management software, and research methodologies. Automated Machine Learning (AutoML) is a core tenet of AI with respect to its flexibility, efficiency, accuracy, and low cost in the agricultural sector. In addition to enhancing farmers' skill sets, AI in agriculture ushers in a new era of guided farming, which promises increased productivity and improved quality with little input [5]. Water and fertilizer management are examples of how farmers may benefit from the smart agriculture concept of crop management as explained in Figure 2 using different kinds of sensors. In today's farming operations, sensors for chemicals, pH, wind, rain, temperature, moisture, and sound are routinely used.

In every facet of farming, smart and precision agriculture plays a crucial role. That's where Information Technology (IT) and IoT meet in one place. They want to use the information gleaned from these many sources to plan, predict, and manage agricultural operations in light of their respective ecosystems. Sensors are now everywhere, and they are used to gather all kinds of data. Sensor networks are widely used for data gathering and transmission in this industry. When it comes to SF, information gathered from the surrounding environment is invaluable [5]. Due to the importance of the soil in determining the likely occurrence of a disease, farmers might benefit from receiving early warnings of impending outbreaks based on weather data. A greater emphasis on data use for crop security has the potential to boost yields while simultaneously reducing their environmental effect. A human brain can only take in so much information at once, therefore we need methods that make analyzing this data simpler so that we can use it to make better decisions. Data mining methods are crucial for every serious data analysis project. In order to find the patterns hidden in big data, it is essential to examine the information from a variety of angles. Many other agricultural jobs, such as pest and disease detection, crop yield forecasting, and fertilizer and pesticide application planning, have already benefited from data mining approaches. In addition to their role in crop management, they may also investigate alternative models that contribute to the evaluation of farm management. Agricultural Internet of Things Network Platform for Big Data Analysis is shown in Figure 3. Therefore, gathering this information is a novel input that may substantially improve agricultural productivity [6]. SF is the practice of using ICTs like the internet and mobile phones in agricultural endeavors. The term ICTs is used to describe a wide range of tools used in agricultural technology. These tools include mobile phones, computers, networks, services, and apps that help with data processing, management, and sharing with specific audiences. It paves the way for the incorporation of data gathering and analysis into ICT-based workflows. The European Union (EU) thinks that satellite images, robots for data collecting, and UAVs are the greatest technology and approaches since they can be used to their maximum potential. In the EU cooperation statement on "Information technology for European agricultural and rural regions" from

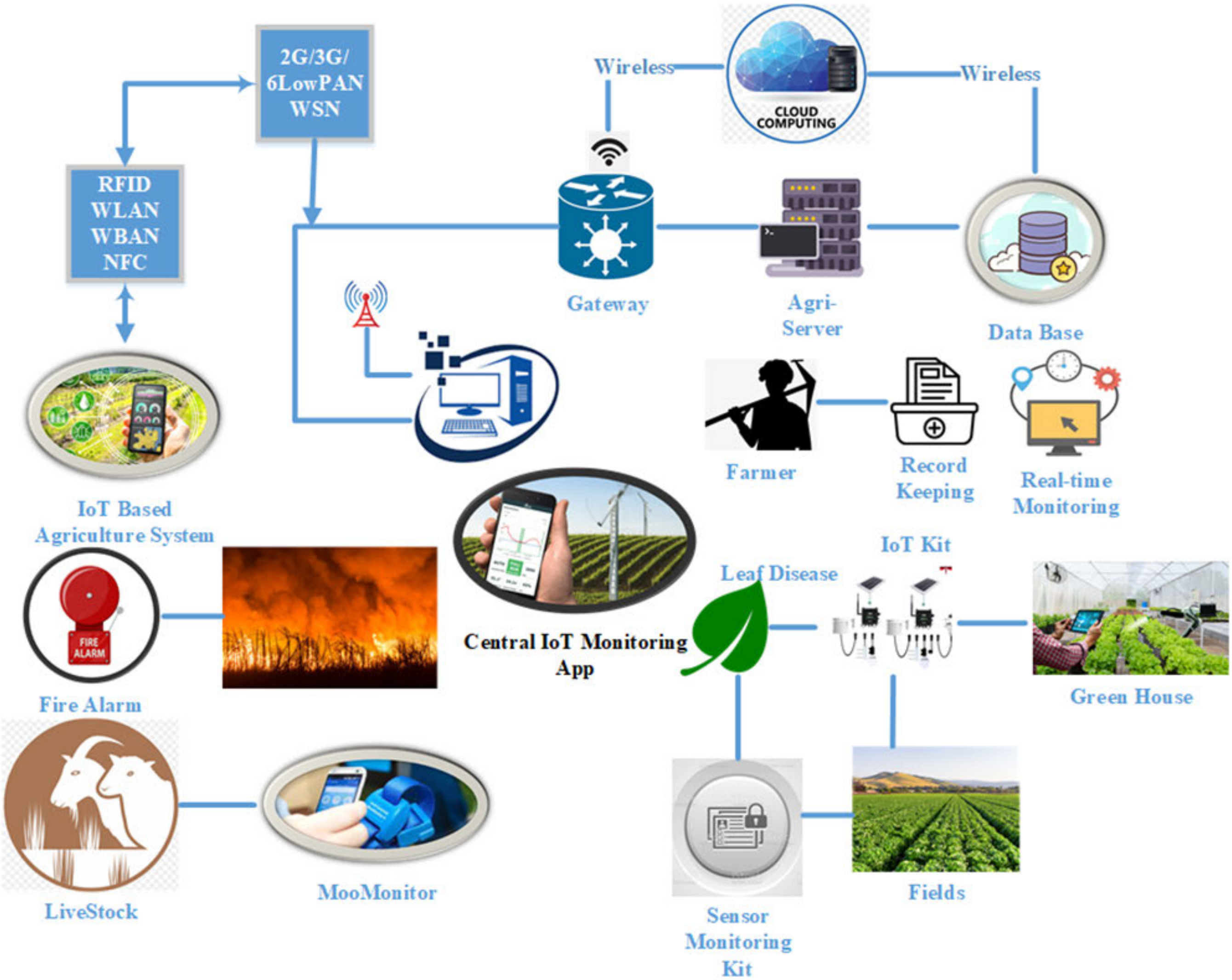

FIGURE 1. **Agricultural trends: Emerging Smart Farming.**

April 2019, 24 EU nations agreed on the importance of smart agriculture in rural areas. According to the SF official proclamation, digital inclusion is the first impediment that must be tackled in places where connection is the largest challenge, such as in rural communities [7]. Only 25-53% of rural areas in Europe had access to Next Generation Access Networks as of the end of 2017, despite IPv6 deployment having been active for half a century. There seems to be an overwhelming amount of efforts aimed towards the digital transformation of agriculture. A new thematic network called Smart AKIS, financed by the European Union, is working to fill this information vacuum in order to develop workable solutions. Even yet, SF shouldn't only aim to make farming as a whole more industrial, but rather to meet the demands of farmers.

Rental schemes for agricultural equipment, provide several benefits, including lower prices for farmers and support systems that mechanize operations. One interpretation of this program is that it encourages the use of Smart Agriculture (SA) in low-income areas. French company trying to modernize inflexible infrastructure by integrating web and hardware technologies. Many farms may access the data, which serves as a resourceful resource library for scientists [8]. By using blockchain technology, AgriOpenData offers a Decision Support Services (DSS) with its other supported services. Reduced water use and increased productivity are just two of the many benefits that robotic agriculture may bring to the farming industry. Finally, a revolution in traceability is taking place thanks to digital ledgers. No matter how far out in the future you want to take it, questions about the safety and reliability of food sources remain an important reality check for any society. The French retail giant Carrefour is considering blockchain technology as a way to boost consumer and industry confidence in the veracity of its transactions. As an example of the flexibility of the blockchain, Hectare Agritech's farm trade platform makes use of the technology in a variety of ways [9].

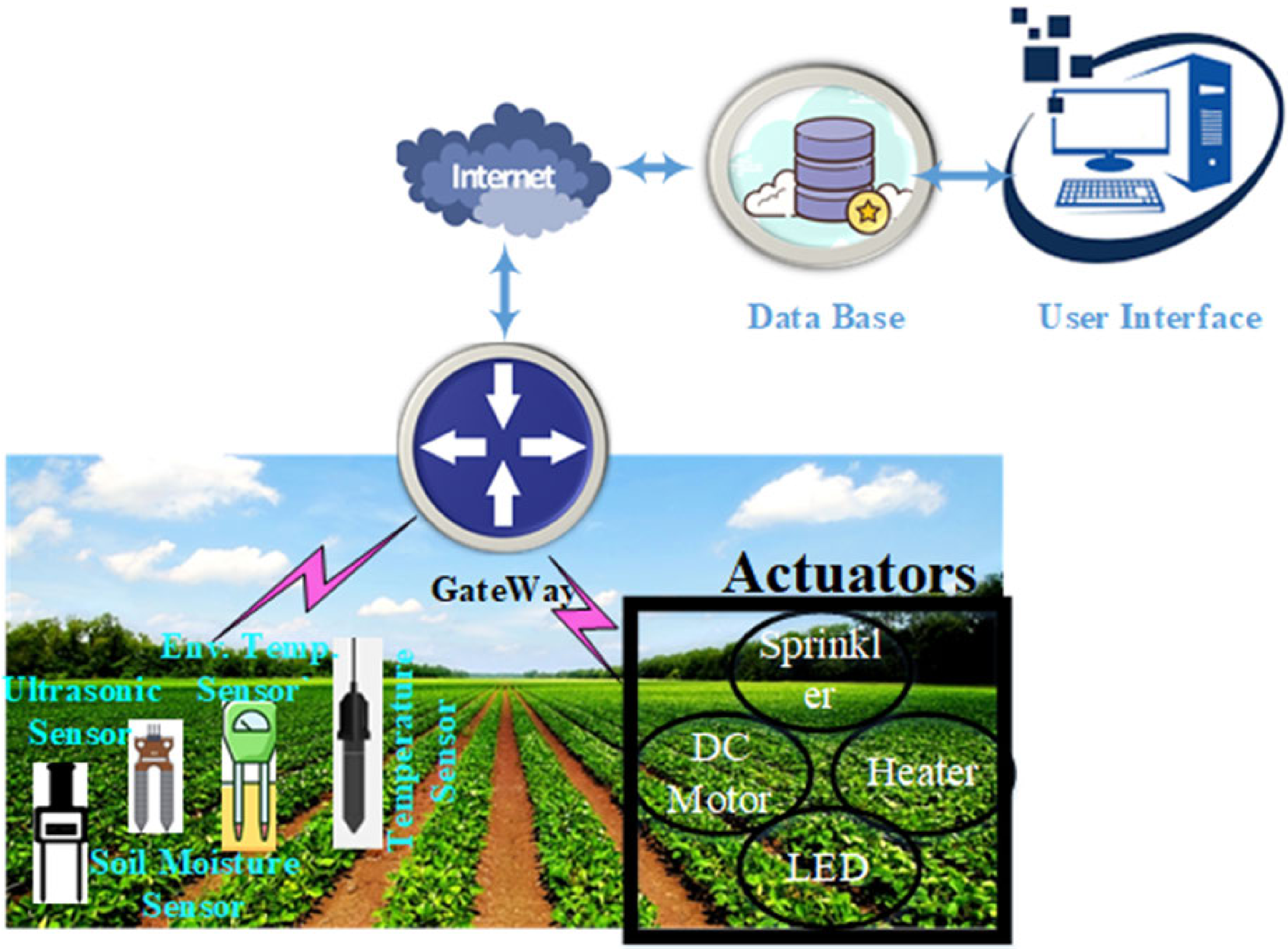

FIGURE 2. Online monitoring and Control of IoT-Enabled Smart Farming.

Depending on the capabilities of the appliance, the edge may contribute a single or several resources. Some gadgets can just send and receive data, while others can do intricate functions. Programmable gateways' power lies in their capacity to interpret data, make judgements, issue instructions to devices, and upload data to the cloud. Though the big data, world will soon be faced with a deluge of information from perception devices, processing this data in the cloud is prohibitively expensive [10]. Costs associated with cloud computing, bandwidth, and initial investment are quite high for some of the suggested solutions. It may be helpful to use a powerful gateway with some processing done at the periphery. It may be possible to reduce the farm's operating costs by moving some subsystems to the periphery. Network bandwidth is conserved and battery life is protected when data is downloaded or processed at the edge. The cloud's ability to store vast quantities of data and run processes and make judgements in real time paves the way for collaborative decision making amongst users. High-tech AI and pattern recognition techniques may be required for processing massive data.

B. NEED FOR INTELLIGENT AND AUTOMATED FARMING

A growing population and changing environment have complicated efforts to increase food production. The agricultural sector, in order to protect itself from the risk of fluctuating markets and to better take advantage of land and water management techniques, must clearly adapt its existing production and adoption strategies. A number of recent IT developments have ushered in a data-driven age for the agricultural sector. India is primarily an agricultural economy, with agriculture contributing 16% and 10%, respectively, to GDP and exports. Roughly 75% of India's people rely on agriculture for their livelihood. Tomatoes are grown on over 3,50,000 acres of land in India, making the country the third-largest producer of tomatoes in the world [11]. More than 15% of India's crops are lost every year due to diseases, which has a negative impact on the country's GDP. Agricultural activities now use more than 40% of Europe's fresh water and are responsible for over 10% of the continent's greenhouse gas emissions. The water usage breakdown for each sector is illustrated in Figure 4. Increased market penetration for fruit crops often requires the use

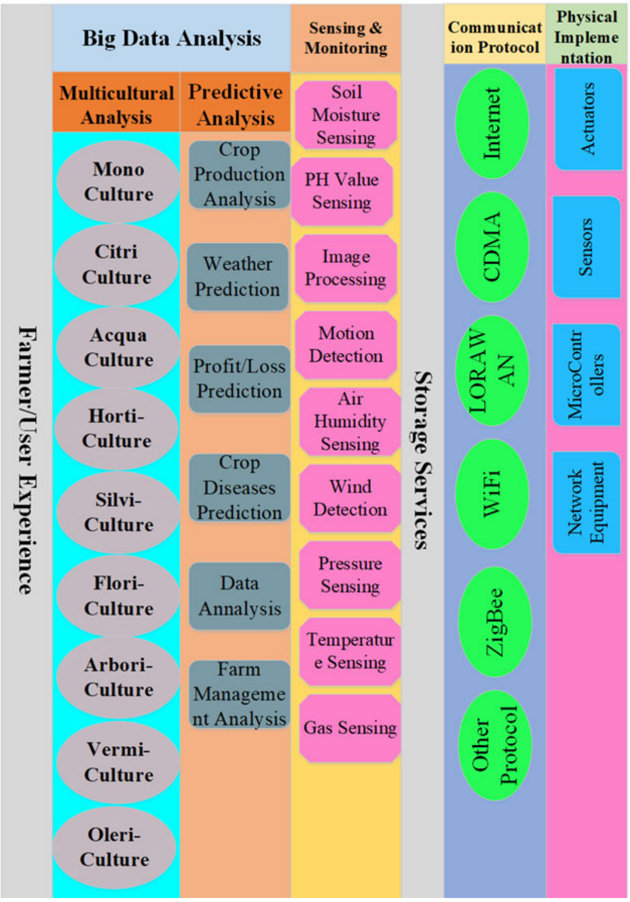

FIGURE 3. Agricultural internet of things network platform for big data analysis.

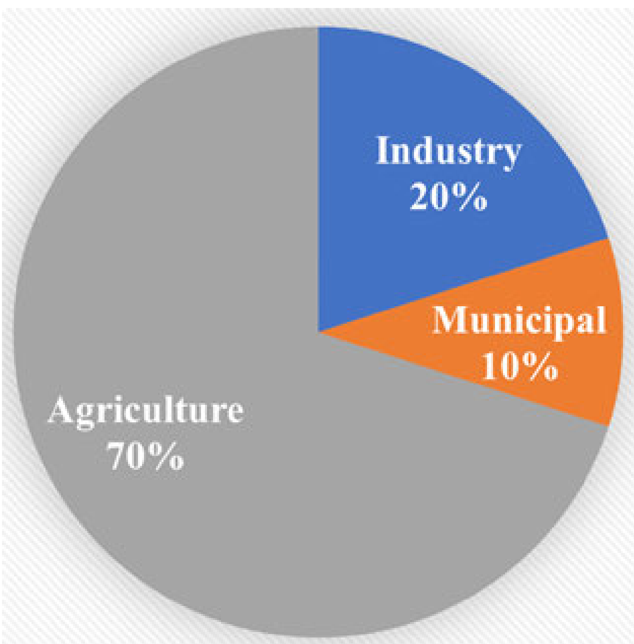

FIGURE 4. Percentage of water consumption in different sectors.

of chemical treatments (pesticides), which has far-reaching consequences for pollinators and the global ecosystem. Over eighty percent of the average human diet consists of plant-based foods. Therefore, there is a rising need for innovative strategies to lessen the burden on water supplies and enhance the efficiency of pesticide applications. Given the challenges posed by factors like climate change, population expansion, and food insecurity, there is an ongoing need to find new strategies to boost agricultural output. More and more people in the IT world consider agriculture as a front-runner when it comes to the development of AI. Because of how challenging or impossible this task is for people, we need to use automated techniques and technologies to help with the decision-making. Innovations in computer vision and precision agriculture have the potential to boost yields and quality while decreasing labor expenses. Access to timely data on crop health and disease hotspots allows for more precise disease control and more targeted treatment.

C. RESEARCH CONTRIBUTIONS

Significant contributions of our study include:

1) This paper covers the fundamental methods for automating pre-harvest agricultural tasks such as land and seed preparation, disease detection and weed control, pesticide, yield and irrigation management.
2) To recap about how ML and Deep Learning (DL) have been used to better detect disease in plant leaves and fruits. Other methods, such as image processing, are also covered, along with the importance of IoT and smart agriculture, drones, and increasing agricultural yields.
3) In this paper, we examine the symptoms of numerous diseases, and infections found in crops. The process of automated plant disease detection and categorization is outlined, along with the many tactics and algorithms that may be used at each stage.
4) The potential and discussion of the future of these ML models for smart agricultural tasks are discussed in this in-depth research, as are the difficulties and obstacles that have prevented their wider implementation to far.

D. OUTLINE OF THE PAPER

The subsequent sections of the article are as follows. In Section II, an overview of basic terminologies and concepts of machine learning are highlighted while in section III the primary focus is on machine learning application in the area of smart agriculture and precision farming. This section highlights automating pre-harvest activities, including soil and seed preparation, disease monitoring, crop analysis, irrigation, and pesticide management. The section also covers various diagnostic signs for plant diseases, ranging from those impacting tomatoes, rice, and apples to other plants. Detailed explanations are provided for image-related processes like picture capture, data processing, image segmentation, extraction, and disease classification, with a strong emphasis on ML and DL techniques. It also covers machine learning applications in harvesting and post

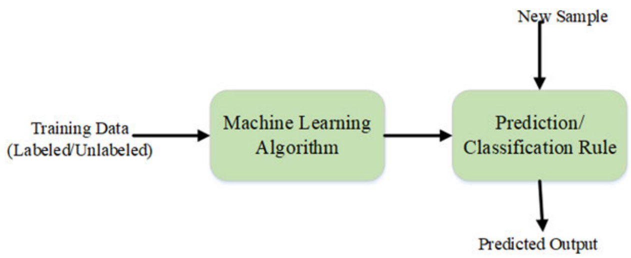

FIGURE 5. Common approach used in machine learning.

harvesting stage. Moving on to Section IV, the article addresses the challenges associated with utilizing ML and computer vision for plant disease detection and classification, along with identifying research opportunities based on the analysis of existing frameworks. Lastly, Section V provides a conclusion of pertinent literature and the issues uncovered during the research presented in the article.

II. MACHINE LEARNING

A. MACHINE LEARNING TERMINOLOGY AND DEFINITIONS

Learning is the basic methodology in most ML approaches, with the goal of gaining the necessary experience (training data) to successfully complete a task. A collection of characteristics, often called features or variables, is typically used to characterize a single instance. Nominal features are those that are enumerated, binary features that are either 0 or 1, ordinal features that are either A or B, or numeric features that have a specific value between 0 and 1. (integer, real number, etc.). To gauge how well an ML model performs on a given job, we may look at its performance metrics, which become better the more data it processes. The efficiency of ML models and algorithms may be estimated using a number of different statistical and mathematical approaches. When the training phase is complete, the learned model may be put to use to make predictions or group together fresh data (testing data) based on what it learned in the training phase. There are a number of statistical and mathematical models that may be used to estimate how well a ML model or algorithm will perform. After the training phase is complete, the learned model may be put to use to make predictions or group together fresh data (testing data) based on what it learned in the training phase. Figure 5 depicts a common ML strategy.

B. TASKS OF LEARNING

Based on the nature of the learning signal used, ML tasks may be broken down into two broad categories: supervised and unsupervised learning. Data are supplied with sample inputs and the related outputs in supervised learning, and the goal is to develop a general rule that maps inputs to outputs. Sometimes in a dynamic setting, only some of the inputs may be accessible, while some of the desired outputs will be absent or provided just as feedback to the actions (reinforcement learning) [12]. The trained model is used to make predictions about the test data's missing outputs (labels) in a supervised scenario. However, with unsupervised learning, the data is not labelled, hence there is no classification needed to separate the training and test data. The learner analyses facts in an effort to establish a precedent for future discoveries.

C. ANALYSIS OF LEARNING

Dimensional reduction is a method used in both supervised and unsupervised learning to simplify the learning process. Its main goal is to create a compact representation of a dataset with fewer dimensions while preserving as much original information as possible. This step is usually done before applying a classification or regression model. Common techniques include principal component analysis, partial least squares regression, and linear discriminant analysis.

D. LEARNING MODELS

Some of the ML learning models that have been deployed are briefly explained as follows:

1) CLUSTERING

Unsupervised learning models, like clustering are often employed to discover meaningful categories in large amounts of data (clusters). Proven clustering methods include the k-means method, the hierarchical method, and the expectation maximization method.

2) INSTANCE BASED MODELS

Memory-based Instance Based Models (IBM) compare fresh examples to cases in the training database in order to learn. Instead of keeping track of a collection of abstractions, these methods produce classification or regression predictions based on individual instances and then test their hypotheses against the data [13]. The complexity of these models increases as more data is added, which is a drawback. In this area, the k-nearest neighbor, locally weighted learning, and learning vector quantization are the most often used learning algorithms.

3) DECISION TREES

Decision trees (DT) are tree-like models for classification or regression. A tree graph is created with a hierarchical organization of the dataset into smaller, more similar groups (sub-populations) using DT. A pairwise comparison on a chosen characteristic is represented by each internal node of the tree structure, while the comparison's conclusion is represented by each branch. If you trace a tree from its root to its tip, you'll end up at a leaf node, which represents the conclusion or forecast made along the (expressed as a classification rule) [14].

4) ARTIFICIAL NEURAL NETWORKS

There are two types of Artificial Neural Networks (ANNs): the more simplistic Traditional ANNs and the more complex Deep ANNs. ANNs are motivated by the capabilities of the human brain, modelling its pattern-generating, cognitive, learning, and decision-making abilities. There are billions of neurons in the human brain, all communicating with one another to take in and organize incoming data. Like the biological neural network, an ANN is a model of the structure of the network reduced to its essentials, consisting of processing units coupled in a predetermined topology [15]. The following nodes are among those that have been placed in hierarchical fashion.

There are three main parts to a neural network:

1) The input layer, where data is brought in.
2) The hidden layers, where learning occurs.
3) The output layer, where the judgement or prediction is provided.

5) SUPPORT VECTOR MACHINES

Founded on the principles of statistical learning theory, Support Vector Machines (SVM) were first introduced in [16]. SVM, in essence, operates as a binary classifier employing a linear separating hyperplane to categorize data points into two distinct groups. The application of the kernel trick facilitates a substantial enhancement in the classification capabilities of conventional SVMs by transforming the original feature space into a higher-dimensional counterpart. SVMs find utility in various domains, encompassing classification, regression, and clustering tasks. What makes SVMs particularly fascinating is their reliance on global optimization techniques, enabling them to effectively address over-fitting challenges commonly encountered in high-dimensional settings [17].

III. MACHINE LEARNING IN SA AND PF

In the future, farmers will be able to produce the same quantity of food while using less water and fewer pesticides. Farmers, in an era of rising output and falling costs, are naturally tempted to maximize both quantity and profit, but the public is increasingly demanding healthy options. The agricultural sector actively seeks for novel goods, methods, and technology. Precision agriculture allows farmers to adapt their practices to a wide range of customer demands. Agricultural progress depends on the use of several tools for data gathering and analysis. Massive volumes of information are created by many of these new technologies, particularly web technologies, and made available to everyone. The most important aspects of data mining for PF are: To efficiently and quickly delve into this data, it is crucial that we be able to handle massive volumes of information and a wide variety of data types (including sensors, pictures, strings, integers, etc.) are required for usage in SA [18]. Whether it's farming techniques or technological advancements, the globe is always improving. Both past information and the use of computer vision technologies are crucial to performance in order to keep up with the expanding agricultural demand. Although it does have an impact on crop categorization, agrochemical production, disease diagnosis, and prevention, it is not a guarantee.

With the correct setting and item, everything is possible. PF is a more exact and regulated alternative to traditional agricultural methods that eliminates labor-intensive, time-consuming tasks like weeding and planting [19]. Precision agriculture include the use of satellite GPS and its applications to livestock. Also, it coordinates, integrates, measures, and analyses a number of technologies in order to boost production and reduce costs [20]. If soil conditions, available acreage, and equipment were to stay constant, agricultural profits and output would increase dramatically [21]. Image and computer vision have flourished in recent years as a result of falling prices for necessary hardware, rising computing power, and a commensurate decrease in the willingness to use destructive approaches [22]. ANNs and fuzzy controllers are two examples of AI based technologies that have arisen in the past two decades to improve the accuracy of climate management in artificially controlled greenhouses. These self-driving, wheeled robots have several uses in the agricultural sector. Robots in agriculture may learn new techniques to help them with their work since farming is an ever-changing activity. The sensors on an autonomous robot are its defining feature since they provide data back to the brain. The robot's command structure might be governed by fuzzy logic.

In most cases, farmers will follow the procedures outlined below while carrying out agricultural operations:

- Phase 1: Choose crop
- Phase 2: Preparing the Land.
- Phase 3: Planting the Seeds.
- Phase 4: Watering and fertilizing the soil.
- Phase 5: Crop Maintenance (Pesticide Application, Plant Pruning, etc)
- Phase 6: Harvesting.
- Phase 7: Post Harvest.

By using the aforementioned approach, agricultural operations may be broken down into three broad classes. These three categories of agricultural work are shown in Figure 6. The next sections provide a comprehensive overview of the most up-to-date methods for using machine vision systems for categorization and object identification prior to harvest.

A. PRE-HARVESTING

Real crop growth is affected by pre-harvest circumstances. During the pre-harvest phase, machine learning is used to keep track of the state of the soil, the quality of the seeds planted, the amount and timing of fertilizer used, the timing and method of pruning, the crop's genetic makeup, and its environmental and environmental conditions. Reduced manufacturing losses need meticulous attention to each individual component. In this part, we examine a few crucial pre-harvesting components and the ways in which ANN and ML used to capture the properties of each.

1) SEED AND SOIL

Soil attribute categorization and evaluation help farmers in significantly lowering on fertilizer expenses, significantly

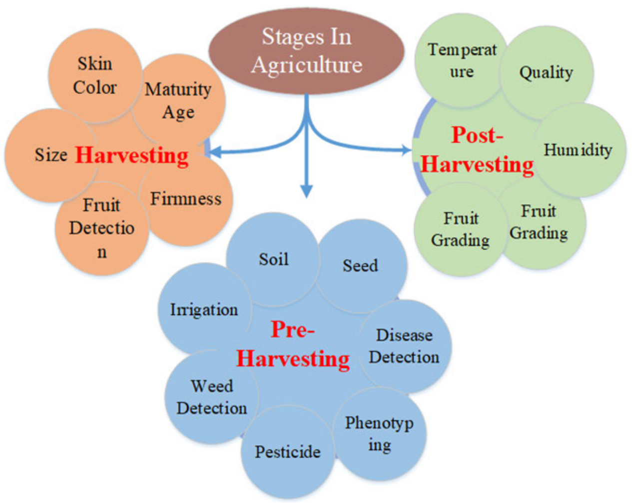

FIGURE 6. Broader Classification with key factors considered for every agricultural endeavor.

reducing on the requirement for soil analysis specialists, boosting profits, and enhancing soil health. Suchithra and Pai [23] established a methodology for classifying and predicting pH and soil fertility metrics. Authors anticipated pH and Soil Organic Matter (SOM) parameters in paddy soil since they are important indicators of soil fertility. In [24] author have made predictions for the soil's organic carbon (OC), nitrogen, and Moisture Content (MC) characteristics. Germination rates are a good indicator of overall seed quality, which in turn has a major impact on harvest success. Many computers vision, ML, and ANN techniques have been shown to have applications in automated seed sorting and soil quality assessments by [25] and [26]. Summary of some of the review work related to the seed and soil is presented in Table 1.

2) MONITORING AND PREDICTING CROP DISEASES

Infectious diseases may easily spread to plants because of their constant exposure to the elements. The susceptibility and state of the crop will determine how quickly the disease spreads. To protect against losses in crop production and quantity, proper identification of plant diseases is essential. Everything from the plant's leaves, stems, seeds, and roots to the plant's blooms, fruit, and seeds [30]. Therefore, in many areas of the world, early diagnosis is difficult [31]. Improvements in DL and Computer Vision (CV) are allowing smartphones to be used in a diagnostic role. Due to the time-consuming nature of manually identifying and counting disease cases across huge populations of crops on big farms, automation is useful for reducing risk. Most illnesses are too minute for the human eye to be able to detect, making medical aid is essential even in underdeveloped nations. Since it was difficult to identify between many species just by looking at images, the use of image processing software to support in the classification of plant diseases became an acute problem.

Variations in soil conditions and nitrogen levels have a significant role in the success or failure of agricultural activities. In the past, pesticides were spread uniformly throughout the field in all squares. Overly conservative water budgeting by farmers could have a dramatic impact on the diversity of pollinator species available to support plant and animal life. When used with analytical tools, ML may help determine the state of a crop's health. The information is used to zero in on the regions with the most severe infestations, enabling farmers to concentrate their pesticide applications there. The ability to modify one's surroundings may have a major impact. Plantix, a German startup, is one such company that uses ML and picture identification in a mobile app to detect plant illnesses and nutritional deficiencies. Modular equipment like this is vital to smaller farms. When it comes to gathering visual and thermal data, larger corporations rely on digital platforms linked to IoT devices. A popular example of a company that uses this strategy is Gamaya, a Swiss firm. By using ML, businesses may focus on disease prevention rather than detection in their efforts to maintain healthy agricultural yields. Some farmers choose to send their soil samples direct to Trace Genetics for analysis, so they may find out in advance how healthy their soil really is. This article provides a comprehensive review of the most up-to-date methods in computer science for automating agricultural disease diagnosis and detection.

3) CROP DISEASES DETECTION AND CLASSIFICATION USING CONVENTIONAL DATA MINING METHODS

Several crop disease detection and classification techniques are available for use in CV. Using DNNs, [32] was able to attain a 99.53% accuracy rate for identifying the plant illness. In addition, neural networks have been used to solve rice-related problems, such as disease diagnosis [33]. In [34] showed that color and texture were useful in identifying diseases in agriculture and horticulture via the discovery and classification of visual similarities. The New Enterprise To monitor crops and alert farmers of any problems, Proper built a system with connected cameras, sensors, and a ML algorithm [35]. Focusing on plant disease, [36] used neutral network processing algorithms to hyper-spectral data. The multilayered neural networks employed by [37] to detect yellow rust in wheat. With the help of ANN software, student achievement went from 95% to 99%.

Tomato crop disease classification dataset based on an experiment by [38], who collected six different tomato leaf types from Plant Village. VGG16 was able to correctly classify 13,261 image signatures (97.29%) while AlexNet achieved 97.50% accuracy. Diseases in plants are easier to spot in their early stages of development, when machine vision approaches are most effective [39]. The first step is to gather and prepare a sample for analysis. Accuracy rates of 87.9%, 87.5%, and 90.15% were achieved when using ML on rice [40], papaya [41], and chilli pepper [42]. In [43], researchers employed the SVM classifier to identify grape leaf diseases. There was an 88.89% success rate in identifying mildew grape plants in [44]. The researchers in [45] found disorders on citrus fruits such as anthracnose

TABLE 1. Soil and seed analysis prior to harvest.

Comparing models, techniques, and methodologies	Best models, techniques, and methodologies	Feature	Utilized Dataset	Results	Ref.
Various activation models for the Extreme Learning Machine (ELM), include sine-squared, Gaussian radial basis, triangular basis, hyperbolic tangent, and hard boundary	Gaussian radial basis function ELMs	Soil	Does not possess (common)	Accurate 80 percent	[23]
Four models for ML, Partial Least Squares Regression (PLSR), ELMs, Least Squares-Support Vector Machines (LS-SVM), and The Cubist Regression Model (CRM)	ELMs	Soil	Possess	more accurate (R2 = 0.81)	[27]
Principal Component Regression (PCR), LS-SVM, Cubist, and PLSR	Best by Cubist is True-Negative TN, the finest LS-SVM for MC and OC	Soil	Possess	MC—RMSEP:0.45,RPD:2.24, TN—RMSEP: 0.071 and RPD:1.96	[24]
Ensemble learning, GoogLeNet, SVM,K-Nearest Neighbor (KNN), Logistic Regression (LR), and Speeded Up Robust Features (SURF) algorithm to classify the extracted features, VGG19	GoogleNet	Seed	Possess	95%	[25]
Based on deep features collected using self-designed CNN and ResNet models, SVM, PLS-DA, and LR models	self-design CNN 80%	Cotton Speed	Possess(China)	80%	[26]
DeepSort	DeepSort	Maize Seeds	DeepSort, (SVM), (LR), and Random Forest (RF)	cross-validated five times	[28]
Binary Logistic Regression (BLR), single feature models, multilayer perceptron (MLP)	BLR, and (MLP)	Pepper Seeds	Possess	90%	[29]

and canker. Citrus trees, especially those bearing lemons and grape fruits. Research findings got a 95% accurate rating in the real world. Exhibits by the writers proved categorization accuracy of around 90% on average [46] while using a big data collection to identify diseases. The Writers in [47] developed a method for identifying potentially harmful tea crops, as well as identifying three distinct illnesses with just a few available traits, and claiming an accuracy rate of 90%. In [48], authors built a technique to evaluate illness presence by using a fuzzy classifier on images of wheat crops. Its precision that 56% of the time, it was possible to distinguish between sick and healthy leaves and as a percentage, they each account for 88%. In [49], the K-Nearest Neighbors (KNN) classifier is used to conduct a comprehensive analysis of agricultural disease identification. The GLCM feature extraction method was utilized by the authors [50]. Utilizing the KNN classifier for Grey Mildew, a disease that affects cotton crops, we were able to increase accuracy to 82.5%. Quantitative and qualitative information about plants. An ANN classifier for the diagnosis of illnesses is provided in [51]. The algorithms RF, SVM, DT, KNN, NB, and KNN from the supervised machine learning family were studied by the authors [52]. CV techniques for determining the most effective algorithm for categorizing plant diseases. Overall, the RF algorithm was 89% effective precision as compared to comparable algorithms.

Similarly, DL approaches outperformed ML methods while evaluating citrus plant disease identification in an evaluation of SVM, RF, SGD, and DL by the authors [53]. Work [54] sheds light on several Plant Diseases (PD) that may affect plants, as well as advanced ML and image processing methods for diagnosing PDs. The goal of [55] was to modify and evaluate state-of-the-art deep Convolution Neural Network (CNN) for image-based PD characterization. The KNN classifier was suggested by [56] as a means of plant leaf disease detection (PLDD) and characterization.

Another paper proposing an intensity threshold approach for tracking cherry powdery mildew's spread is [57]. In [58], a hybrid approach to disease detection and identification in citrus trees is given. In order to identify the infected areas of previously identified mandarin leaves, the authors provide a color-based method [59]. Author in [60], proposed CNN approach to identify bean diseases. Wheat disease detection studies are conducted in [61], while banana field imaging studies are conducted in [62]. SVM was shown to be the most effective classifier in [63], which presented a technique for separating rotting apples from healthy ones. Using KNN and SVM, the authors of [64] looked for signs of leaf deficiencies and illnesses. It is advised in [65] that a hybrid approach be used to identify and classify illnesses in citrus plants. The state-of-the-art review efforts for smart disease diagnosis in SF are summarized in Table 2. The different phases of grape leaf disease are shown in Figure 7.

4) CROP DISEASES DETECTION AND CLASSIFICATION USING MULTIMODAL CROP DATA ANALYSIS

In [77], the authors used a hybrid approach, combining data from hyperspectral and multi-spectral imaging, to identify illness at an early stage achieved a precision of 94.5%. These writers suggest a better data-driven choices may be made with the help of Hydra's multi-valued data fusion, application event detection, and other features [78]. There are a variety of ways to classify the elements: All the way from the ground up to the upper altitudes. Once again, there are a variety of ways to stratify the data. Two with the help of Embrapa, the SA Domain one offered facts and figures about top-performing methods that are helpful to farmers, and the other is data that may assist them implement such methods. Use them for water collection on a small scale. The first action was to determine whether or not a threshold amount of moisture existed. In the second stage, enough irrigation time was calculated by the monitoring of crop evaporation [78]. Figure 8 shows a representational sample of infected apple leaves with varying degrees.

5) CROP DISEASES DETECTION AND CLASSIFICATION USING DL

In this part, we will look at different DL approaches used to modernize farming. Using the DL framework developed at Berkley's vision and learning center, a model for identifying plant diseases was developed in [79]. The model

TABLE 2. Summarized review related to traditional data mining techniques for illness detection and classification.

Techniques	Model used	Plant	Disease features	Obtained Results Accuracy (%)	Authors and year	Reference
Image processing by SVM	Supervised Learning	Grapes	illnesses that affect leaves include powdery and downy mildew	88.99	Padol and Yadav, 2016	[66]
	Supervised Learning	Cotton	The illness of leaf spot	89	Patil and Zambre, 2014	[67]
	Supervised Learning	Apple	blotch, rot, scab	93	Dubey and Jalal, 2012	[68]
Image processing	Neural Network	Cotton	Red leaf spot, cercospora leaf spot, and alternaria leaf spot which affect leaves.	89.56	Warne and Ganorkar, 2015	[69]
	Neural Network	Cotton	illnesses that cause leaf spots	98.1	Revathi and Hemalatha, 2012	[70]
Image processing	Artificial Neural Network	Potato	Late blight of the leaf	100	Kaur and Singla, 2016	[71]
Image processing	Back-propagation Neural Networks	Grapes	illnesses that affect leaves include powdery and downy mildew	100	Sannakki and Rajpurohit, 2013	[72]
GoogLeNet	Convulution Neural Network	Multiple Plants	Illness in plants	96.17	Barbedo, 2019	[73]
AlexNet precursor, VGG 19, inception, DenseNet, ResNet, PlantDiseaseNet, SVM BPAlexNet GoogLeNet, ResNet-20 VggNet-16	Neural Networks and Supervised Learning	Multiple Plants	illness of leaf	97.62	Liu and Zhang, 2017	[74]
Fuzzy rule-based approach for disease detection (FRADD)	Fuzzy logic	Apples	Illness of fruits	91.66	Kour and Arora, 2018	[75]
K-nearest neighbour (KNN), support vector machine (SVM), extreme learning machine (ELM), VGG16, VGG19, and AlexNet	Supervised Learning	Multiple Plants	detection of plant pests and illnesses	98	Türkoglu and Hanbay, 2019	[76]

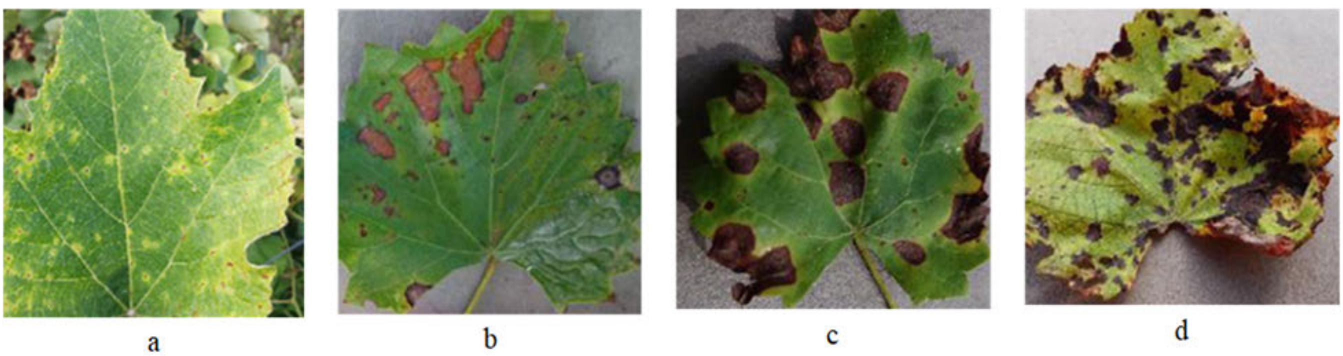

FIGURE 7. Different phases of grape leaf disease from healthier (a) to fully affected (d).

has accurately diagnose 13 unique diseases. The method proposed in [80] combines CNNs with K-means features for the purpose of preventing and detecting plant diseases. Using DL and K-means improved identification accuracy to 92.89% [81]. Current research on automated disease diagnosis using DL in agriculture is shown in Table 3.

The study in [82] utilizes a Deep Convolutional Neural Network (DCNN) based on the AlexNet architecture. The proposed model underwent comparison with alternative CNN models, specifically VGG-16 and Lenet-5. The results of the comparative analysis indicate that our AlexNet-based model exhibits superior accuracy when compared to VGG-16

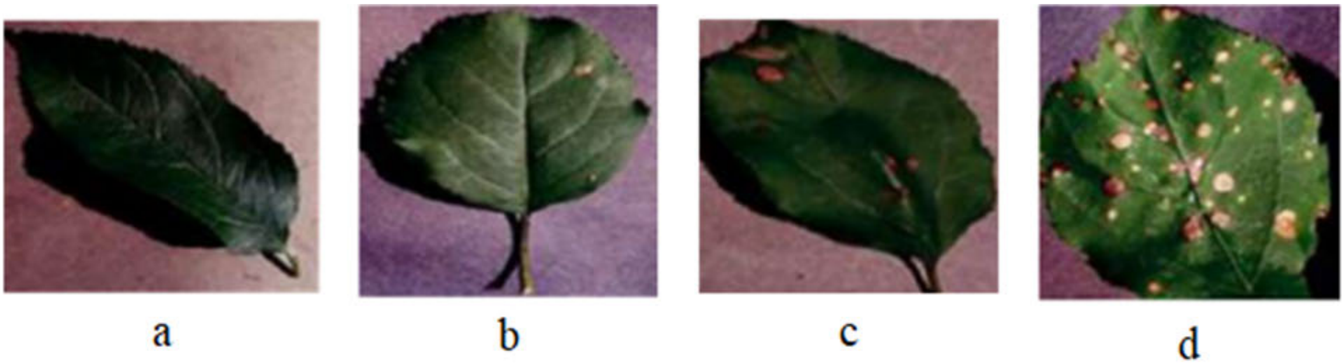

FIGURE 8. Different phases of Apple leaf disease from healthier (a) to fully affected (d).

and Lenet-5. Research in [83] utilized a dataset comprising a total of 7070 images, encompassing both diseased and healthy leaves and CNN was used to mitigate the diseases. The dataset was sourced from the plant village repository. The proposed methodology demonstrated a high level of accuracy, successfully identifying crop species with a precision of 96.76 %. The investigation in [84] introduces a novel approach which explores the application of ant colony optimization (ACO) to enhance disease detection, encompassing key phases such as data acquisition in the form of image then classifying the image and improving the image quality for more accurate data training.

In [85], authors addressed the challenge of small image databases by introducing a deep Siamese convolutional network. This network achieved a recognition accuracy of over 90 % for three grape leaf diseases: Esca, Black rot, and Chlorosis. In [86], a thorough analysis and comparison of different ML based classification techniques is performed, the RF algorithm emerged as the most suitable model, attaining a 79.23 % accuracy for plant disease prediction. In [87] author conducted a comparative study of five architectures for disease recognition. Their findings revealed that ResNet50 outperformed others, achieving 94 % accuracy on the test set. In [88], the paper explores classification methods that rely on input data, employing k-mean clustering and Support Vector Machine. The challenge of method selection is acknowledged due to varying results based on input data. Disease detection, particularly in coffee leaves, is addressed in [89] using Convolutional Neural Network (CNN). CNN demonstrates effectiveness in image classification and pattern recognition, specifically in identifying coffee leaf diseases with high accuracy. Despite the method's time-intensive nature, it proves advantageous in achieving accurate detections compared to alternative approaches. Author in [90] proposed an approach for early-stage identification and categorization of tomato leaf disease. Utilizing the AlexNet framework and KNN, it achieves improved accuracy, yet the KNN algorithm's slowness remains a drawback. In [91] DL-based approach for tomato leaf disease detection, employing a residual network and CNN classifier is presented. Despite achieving enhanced accuracy, the method is deemed economically inefficient.

The authors of [92] employed DL to identify powdery mildew (PM). While ResNet-50's 98.11% CA was the top for differentiating between healthy and sick leaves, AlexNet's 95.59% CA was the highest for processing 2320 photos in the shortest amount of time (40.73s) [93]. Both AlexNet and SqueezeNet were tested for their ability to identify disease in tomatoes by the authors of [94], and both were found to have comparable accuracies. Diseases in cassava have also been identified using GoogLeNet (Inception) [95], [96]. The last study, [97], examined two variants of the ResNet algorithm for disease detection in tomatoes and found that ResNet-50 was superior to ResNeXt-50.

6) CROP PHENOTYPING

Phenotype refers to the sum of an organism's observable traits. Personality, biological characteristics, physical attributes, and appearance may all be considered fundamental traits. Throughout its life cycle, a plant's morphological qualities remain consistent, but its ontogenic, physiological, anatomical, and biochemical properties change [114]. In addition, the phenotype contains a vast array of processes, structures, and functions as it matures and develops [115]. Successful breeding and quick phenotypic assessment are essential for cultivar development. Science confirms that increasing crop output is the primary difficulty in plant breeding. Increase in the number of phenotypic assessments, so alleviating the alleged quantitative constraint for functional genotyping research, are shown by [116] and [117].

Hyperspectral sensor systems come in four distinct flavors: push broom, filter-based, non-imaging, and two. On the other hand, they may be put to use in agriculture to help prevent the spread of a certain illness. The simplex volume maximization method [118] is another well-known example of a collection of mathematical methods used to categorization. Classification and stress phenotyping are two common uses for support vector machine (SVM) techniques [119]. K-means clustering, ANN, Gaussian mixture models, etc., may all be

TABLE 3. Synopsis of the literature on utilizing deep learning to identify and categorize illnesses.

Techniques	Targeted Parameter	Deep Learning (DL) features	Ref.	Author and Year
Convolutional Neural Networks	Cotton Yield	Using photos of commercial farms, CNN was able to estimate the cotton production.	[98]	Tedesco-Oliveira and da Silva, 2020
Deep Convolutional Neural Networks	Crop Yield	Prediction of crop production using deep CNN	[99], [100]	Nevavuori and Maimaitijiang, 2020
Convolutional Neural Networks	Rice Yield	Using UAV-based remotely sensed photos, Deep CNN is used to estimate rice grain yield during the ripening stage.	[101]	Q. Yang and L. Shi, 2019
Convolutional Neural Networks	Crop Yield	Crop Yield Prediction Using DNN.	[102]	Khaki and Wang, 2019
Convolutional Neural Networks	Yield Estimation	Estimating yield in real time using deep learning	[103]	Rahnemoonfar and Sheppard, 2017
Convolutional Neural Networks	Crop Yield	A Self-Predictable Crop Yield Platform (SCYP)	[104], [105]	S. Lee and Elavarasan, 2020
CNN-RNN	soybean yield	Unmanned aerial vehicle (UAV) with dual cameras and a high-throughput phenotyping (HTP) platform for a large-scale soybean yield	[106], [107]	N. Yu and Z. Chu, 2020
Faster Region-based Convolutional Neural Networks (Faster R-CNN)	Strawberry Yield	Deep Neural Network-Based Prediction of Strawberry Yield Using High-Resolution Aerial Orthoimages	[108]	Y. Chen and W. S. Lee
(CNN-LSTM) combination	Soybean Yield	Deep CNN-LSTM Model for County-Level Soybean Yield Prediction	[109]	J. Sun and L. Di, 2019
	Wheat-Production	Deep Learning Approaches for County-Level Wheat Yield Prediction in China.	[110], [111]	X. Wang and S. Ju, 2020
(CNN-RNN) combination	Crop Yield	Framework for Crop Yield on CNN-RNN	[112]	S. Khaki and L. Wang, 2020
(3D CNN)	Soybean Yield	Soybean crop case study Using Deep Neural Networks for Crop Yield Prediction	[113]	Terliksiz and Alt'yla, 2019

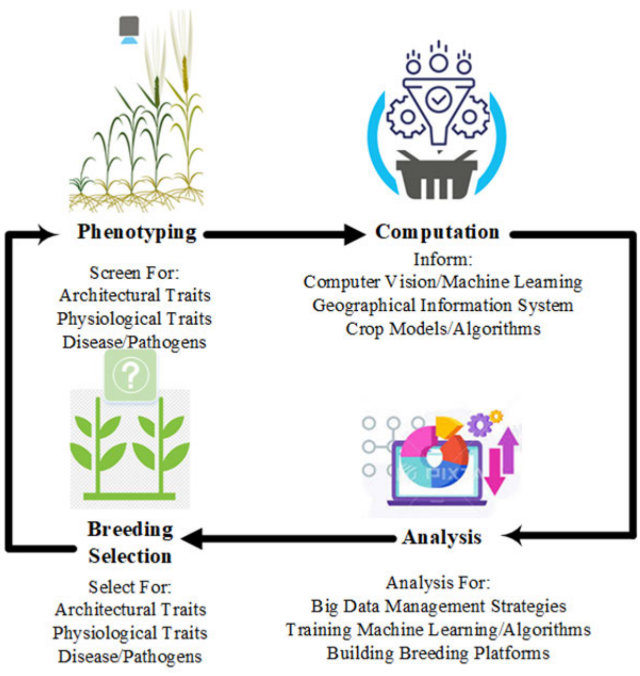

FIGURE 9. Crop phenotyping communication network.

useful, but a deeper knowledge of the process would allow for their more effective use. For example, a telepresence robot equipped with a suite of non-contact sensors may be utilized to conduct strength tests on plant stalks and collect data on the genetic makeup of the plant using an autonomous ground vehicle [120]. As an alternative phenotypic platform, we may use metaphor [121]. This is helpful also because ground vehicle might be equipped with sensors to collect data on certain plants, while the observation tower could keep an eye on a large area and zero in on specific ones. Other methods of accessing or collecting data include remote sensing and ground-based devices [122]. Pre-trained neural networks, or Deep Phenomics, may be used to give plant scientists with phenotyping models right away [123]. Leaf counting, mutant classification, and age regression tests were conducted to assess the efficacy of image-based phenotypic tasks. Imaging and environmental sensors that don't break the bank were the subject of research by [124]. See Figure 9 for a visual representation of the crop phenotyping for communication network.

7) EFFICIENT UTILIZATION OF FERTILIZERS AND PESTICIDES

According to the findings of that research, an annual worldwide application rate of 5.6 billion pounds of pesticides is a realistic estimate. Reducing pesticide use is possible because to pattern recognition and decades of data on crop conditions. With the use of image-based pest control software, spotting these unwanted guests is a breeze, and the same goes for zeroing in on the best way to get rid of them. Since pesticides may be harmful to people if consumed in large numbers, agents help ensure that just the necessary quantity is applied to the crop. Plant diseases, such as fungal and nematode bacteria and rodents, may develop in a variety of environments, including those that are too warm and humid throughout the plant's growth cycle. Agrochemical-containing agricultural goods hit shelves 30 years ago and immediately revolutionized the industry. Pesticides, antibiotics, and insecticides are all examples of modern chemical therapies that have helped farmers combat pests and diseases. Using these pesticides reduces crop damage, although it does so in a variety of ways, some of which are better for the environment and human health than others.

However, so-like neuropeptides are thought to be essential for the proper functioning of all biological and behavioral processes, including metabolism and reproduction, in insects and other animals like mollusks. NeuroPIpred takes in a neuropeptide composition from an insect and produces a novel insect poison that is lethal to but not harmful to other insects. For decades, the use of harmful agrochemicals has been a major cause for worry across the globe.

8) PEST IDENTIFICATION WITH DEEP LEARNING TECHNIQUES

In [133], the authors offer an embedded system with ML functionality, which guarantees continuous detection of pest infestation inside fruit plantations. A low-power embedded sensor device and a neural accelerator form the basis of the embedded solution, which can be used to take and interpret photos from inside the most prevalent types of pheromone-based traps. The results demonstrate how insect infestation may be automated for an indefinite period of time without any involvement from the farmer. By using deep learning methods, a fully automated, real-time pest monitoring system has been developed, with the human out of the loop totally [134]. Over preexisting validation data, the VGG model achieved its maximum accuracy of 93.5%. To minimize the potential for human mistake and shorten the time required to diagnose plant illnesses, Barbedo [135] developed an image segmentation algorithm. Background removal and lesion tissue segmentation are two common pre-processing steps outlined in many articles [136], [137], [138], [139] on image-based plant disease detection.

An 88% identification rate was reported by the authors of, who also offer a technique for detecting illnesses in apple fruit and preventing their spread in a timely manner due to environmental variables. Using an enhanced CNN for real-time identification of the illness using an image dataset, Jiang et al. [140] suggested a CNN model for disease detection in apple leaves. In [141], we see the introduction of a new mobile app that uses a deep-learning technology to automatically categorize pests in order to aid professionals and farmers. Aphids, Cicadellidae, Flax Budworm, Flea Beetles, and Red Spiders are just some of the pests that have been used to effectively verify the research, with the approach displaying an accuracy of 99.0%. In study [142], the authors examine the different strengths of SoA CNN-based object identification models for the task of recognizing beetle-like nuisance insects on nonhomogeneous pictures. Five distinct CNN architectures were used to create a method for disease identification in banana plants by the authors of. Additional state-of-the-art studies related to automated pesticide duties in agriculture are included in Table 5.

9) WEED DETECTION AND MANAGEMENT

Fungus follows the proliferation of weeds to further reduce productivity and profits. Herbicides are the current standard, however there are issues with both their effectiveness and their cost. Second, weeds are becoming more and more resistant to herbicides when they are kept in the soil for extended periods of time. As soon as the technology is fully implemented, it will drastically alter how farmers look for infected areas. See & Spray, developed by California-based company Blue River Technology, is capable of autonomously selecting and treating just undesirable plants with herbicide. The number of chemicals needed is cut by around 80 percent due to this technique. The weed profiling function in See & Spray also helps when it comes to developing individualized herbicide treatment plans. Water use and distribution may be measured with the use of meteorological variables, agricultural factors, and economic factors with the help of data mining. Pest management is crucial in a farming operation. Although, several scholars have used ML to study plant mapping [150], [151]. Many unmanned aerial mapping equipment have been developed for use in optimizing fields. Frying equipment managed by the Internet of Things NB-IoT is able to process and form massive data sets. Additional state-of-the-art efforts on automated weed identification in agriculture are included in Table 6.

10) WATER ANALYSIS FOR SMART AND OPTIMIZED IRRIGATION

ML help in analysing past data to determine how much water each field needs based on its specific moisture content. Before the advent of machine learning, farmers had a hard time determining the optimal amount of water for irrigation. Moreover, the ML robots can monitor the field's moisture levels in real time and apply the right amount of irrigation water to all areas of the field in an isobotonic pattern. Water management is very important in irrigation because its one of the crucial factor for the world's food supply. Almost 70% of the world's freshwater is used for irrigation. As the world's population and food demand rise, this becomes an environmental concern and an issue in international trade. ML-enabled smart irrigation systems, with in-field sensors and satellites, provide accurate measurements of temperature, humidity, precipitation, and crop growth. If given enough information, an irrigation system may become "smart", requiring less efforts and workload to achieve the same

TABLE 4. An overview of the literature on smart agriculture's optimum fertilizer and pesticide usage.

Method	Objective	Used information	Year and Ref.
Neural Networks	a prediction of six different bug kinds in an apple orchard	Digital pest photography	2015, [125]
Rapid Association Rule Mining, Multivariate Regression Mining, and Gaussian Naive Bayes	predicting illnesses and pests	Temperature, soil temperature, humidity level, leaf moisture, and other meteorological information	2011, [126]
Interval Fuzzy Logic	predicting illnesses and pests	temperature and humidity information	2013, [127]
Time series analysis and Random Forest	Pest population forecasting (including dynamics of the population)	Information of pest	2019, [128]
Random Markov Field, Random Forest,	finding weeds or plants that produce beet sugar	Robots' pictures of two distinct fields	2016, [129]
DCNN	finding of weeds	pictures taken at various locations	2019, [130]
SVM	detection and weed and crop categorization	Vegetation pictures	2018, [131]
Naive Bayes algorithm	Control of irrigation and fertiliser dosage suggestions	Weather forecast information and sensor data (temperature, moisture, and PH)	2017, [132]

TABLE 5. An overview of the literature on applying deep learning to determine the optimum application of fertilizers and pesticides in the context of smart agriculture.

Dataset used	Best model	checking precision	No of trainable parameters (Million)	Year and Ref.
Banana leaf photo	ResNet-152	99	60	2020, [143]
PlantVillage	VGG-19	98	143	2020, [144]
	VGGNet	99.5	138	2018, [145]
	GoogLeNet	99	7	2016, [146]
	ResNet-50+SVM	98	25	2020, [147]
PlantVillage dataset, a potato leaf was retrieved	VGG-19 +Logistic Regression	97.8	143	2020, [148]
leaves of the tomato, potato, and maize taken from PlantVillage	CAE	86.8	3.3	2020, [149]

TABLE 6. Techniques for detecting weeds using machine learning.

Model	Precision (%)	problem description	chosen crop	Dataset	Year and Ref.
Random Forest (RF) algorithm	95	detection and categorization of crops and weeds	unidentified	Pictures were gathered from a private farm.	2020, [152]
	96	Canopy structure measurement	Avocado tree	Australia's Bundaberg, an avocado field	2019, [153]
	81	weed identification	Maize	Images were captured in a Belgian agricultural field.	2018, [154]
	87.9	mapping of early weeds	Sunflower, cotton	Mages were captured from a Spanish farm field.	2018, [155]
	92.19	water and aquatic plant monitoring	Stratiotes aloides	Canada's Trent-Severn Waterway in Ontario	2018, [156]
Support Vector Machines (SVM)	84.8	mapping of land cover	9 perennial crops	Images were captured in Australia's NSW state's Riverina area.	2018, [157]
	92.35	Species identification of weeds	8 weed plants	1600 pictures of weeds were taken on a farming field in South China.	2019, [158]
	95	Utilizing the form feature, locate weeds	Sugar beet	Photos shot at Shiraz University in Iran	2019, [159]
	95	species identification for weeds	Soybean	Photos were taken at the Sâa José farm in Brazil.	2018, [160]
	95.5	UAV imaging is used to map weeds.	Sunflower, maize	Pictures were gathered from a personal farm.	2018, [161]
	97	Classification of crops and weed	Chilli	Chilli field images were collected.	2016, [162]

level of water efficiency. ConsertWater, a California based application system, calculates how much water a field needs depending on satellite data, weather, geography, and location. The beauty of the app is that it functions reliably and without installing any sensors on the ground. The app's developers claim that farmers may reduce their water consumption by 30% just by using it. Water quality has been examined, and various techniques for managing water in agriculture have been implemented [163], [164]. In [165] and [166], the author suggests using an automatic irrigation system to investigate farmers' water demands. The quantity of water needed is estimated using the Naive Bayes method. This method considers forecasted weather conditions in order to determine the optimal timing and quantity of water and fertilizer needs for crops.

This literature review explores cutting-edge smart monitoring and irrigation control strategies employed in recent years for irrigation scheduling. Findings of [167] suggest that closed-loop irrigation control systems outperform open-loop counterparts by addressing uncertainties. The integration of soil-based, plant, and weather-based monitoring within a modeling framework, coupled with model predictive control, emerges as a promising avenue to enhance water use efficiency. This comprehensive review serves as a valuable resource for researchers and farmers seeking optimal irrigation monitoring and control strategies to enhance scheduling in open-field agricultural systems.

This study [168] introduces an open-source technology-based smart system for predicting field irrigation needs by integrating ground parameters like soil moisture, soil temperature, and environmental conditions with Internet-sourced weather forecast data. The sensing nodes encompass soil and environmental factors, including soil moisture, soil temperature, air temperature, UV light radiation, and crop field humidity. The system's intelligence relies on a smart algorithm, combining sensed data with future weather forecast parameters. Deployed on a pilot scale, the system wirelessly collects sensor node data over the cloud, providing real-time insights through a web-based decision support system. Offering a closed-loop control option, the fully functional system demonstrates promising irrigation prediction results based on three weeks of data analysis.

In an Algerian study [169], remote irrigation management utilizes a 6LoWPAN wireless sensor network, integrating ZigBee with the internet. Soil moisture data, acquired via SMS, is transmitted through a ZigBee mesh network to a smart gateway. This information is then relayed to a web service through mobile data communication, enabling data evaluation and responsive actions. Additionally, ZigBee technology proves successful in monitoring citrus soil conditions and nutrients within an IoT system, resulting in a 20 % conservation of water and fertilizer resources. In Las Vegas [170], signal-based ET controllers reduced water usage by approximately 20 % compared to control sites. Similarly, effective irrigation scheduling in Valdebebas, Madrid, Spain, using ET controllers based on climatic conditions achieved water savings of up to 35 %.

Utilizing fuzzy logic systems [171], farmers can make informed decisions regarding watering needs. A proof-of-concept IoT-based fuzzy logic control system, integrating temperature, soil moisture, and humidity, demonstrated superior water use efficiency, requiring a 7-hour water pumping period compared to 12 to 20 hours for drip and manual flooding irrigation methods over 3 days.

A smart irrigation system is proposed in [172] where the time of usage (TOU) model is being utilized. The results indicated that both water and energy consumption could be reduced by 7.97%, which equated to a 25.34% reduction in total. It was argued by [173] that the FITRA, a fuzzy neural network based model, would be useful for watering crops, based on collected information algorithm adjusts the flow of irrigation water by analyzing data of sensors to enhance output while minimizing water use. In [174], there is developed method to propose watering schedules. Several prediction models were used in a variety of regression and classification techniques. A unique CNN calibration strategy was presented by the authors [175]. It has a very basic structure consisting of only one convolution layer and one pooling layer. Extracting the most informative characteristics was accomplished in a data-driven manner by using the DT technique.

In order to regulate the switching time of a pump in accordance with user-defined variables, sophisticated fuzzy logic is proposed in [176], along with a framework in which sensors play a vital role and contribute to the system. In [177], an overview of agricultural irrigation systems that rely on the IoT is discussed in detail. In [178], different methods that are used to manage precision irrigation systems are examined in both laboratory and field settings. In [179], [180], the authors suggest an architecture for implementing smart irrigation systems that makes use of LoRaWAN and fog computing. Drone-based remote sensing methods were utilized by the authors of [181], [182], [183], and [184] to identify trees exhibiting symptoms comparable to those of trees infected with PWD. As a whole, the SVM was 6.7% more accurate than the ANN (94.13% vs. 87.43%). The research recommends creating an UAS dubbed AgriQ [185] to carry out precision agriculture. Table 7 provides a summary of more cutting-edge research on automated irrigation management for the agricultural industry.

11) SMART FARMING TECHNOLOGIES: ROBOTICS DRONES AND UAVS

Large-scale farms have substantial labor expenditures. Harvesting also requires a large workforce in traditional plantation agriculture. The profit margin will decrease if the crop is left unharvested for some reason. A robotic harvesting system can detect when crops are ready to be picked and then do it automatically. This is helpful for lowering labor expenses and making sure the harvest is delivered to the client without losing any of its quality. The same ML methods and technologies used in crop production are also present in the cattle industry. Farming is now completely automated and supervised by machines. Combining these data sets can aid in making a more accurate diagnosis or finding signs of damage. Figure 10 provides a good illustration of the overall robotic system used in SA system. Drones may survey enormous regions along predetermined paths. These are also entirely made using CV. Crop analysis, plant monitoring, weed

TABLE 7. Characteristics of research focusing on the irrigation job in smart agriculture.

Technology	Monitoring	Improvement / limitation	Year and Ref.
Naive Bayes	assessment of the specific water need and advice on the required fertiliser	Data from sensors (humidity, soil temperature, and soil PH), and sites that provide weather forecasts	2019, [165]
Decision Trees, GA	forecasting of irrigation events	Julian day, crop, weekday, bank holiday, and climatic data (temperature, humidity, precipitation event)	2019, [166]
Support Vector Regression, Irrigation estimation algorithm and an optimization	cost reduction for irrigation	Information on soil moisture, cloudless irradiance, numerical meteorological data (cloud cover, humidity, precipitation), and data on solar energy	2022, [172]
Fuzzy Neural Network	Irrigation management	sensors for measuring soil moisture	2019, [173]
Linear regression models, Boosted Trees Classifiers, and Gradient Boosted Regression Trees	the forecast for the weekly irrigation plan	Actual irrigation records, weather station data, and previous sensor data	2017, [174]
DM	Zone-specific irrigation management	Sensor data, including temperature, humidity, and other plant data,	2021, [175]
WiFi, Zigbee, and LoRaWAN	monitoring of agriculture and solar panels	technique for monitoring agriculture that uses energy harvesting	2021, [180]
MATLAB	soil and plant morphologies (soil porosity, tree branching, biochar porosity)	GUI-based software (for Windows OS)	2020, [181]
REUTIVAR-App	Management of irrigation, fertiliser, and reused water	It offers suggestions for daily farm-scale real-time irrigated and fertilisation schedules.	2017, [182]
SmartFarmNet (Semantic Web Technologies)	Soil, fertilization, irrigation	Real-time data analytics and a user-friendly interaction approach similar to that used in e-commerce	2017, [186]
OASNDFA	Orange orchards	distributed sensor nodes to measure soil temperature and moisture	2020, [187]
Fuzzy Logic	Irrigation management	Meteorological parameters	2019, [188] 2017, [189]

detection, disease detection, and determining the impact of plant health and drought on crop productivity can all be accomplished with the help of multi-spectral images created from standard photographs. Taking into account all possible yields, this is a fair estimate of the harvest. Robots using machine vision are increasingly employed for tasks like weed picking [190] and chemical application [190]. This estimate of the crop yield is realistic when all possible yields are considered. More common uses for robots using machine vision include weed harvesting [190] and chemical application [190] with pinpoint accuracy.

Drones used for precision farming may operate at varying altitudes. Using a hundred meters of altitude, drone pilots may take high-quality images for automated leaf analysis on maize plants, or they can hover low over a field like a sprayer. The defining characteristics of drones are its ground control station (GCS), data link system (DLS), and flying platform [191]. Depending on their intended function, most agricultural unmanned aerial vehicles (UAVs) fall into one of three categories: rotary-wing, flapping-wing, or fixed-wing [192]. Ag Drones and senseFly are examples of fixed-wing UAVs that farmers prefer over multi-rotor drones for remote sensing because of how quickly they can cover land. Featuring a top-notch camera From 100 meters above ground, they can take high-resolution, georeferenced RGB pictures of hundreds of acres per day. While in flight, multispectral instruments may measure soil moisture and temperature, the number of plants, vegetation indices (e.g., NDVI, MCARI, CCCI, CWSI, NDRE) [193], and even create three-dimensional maps of the landscape. The Lancaster is a well-liked fixed-wing drone because it allows for dependable data gathering from the air and has the broadest array of aerial sensors. Precision imaging and operations are better accomplished with multi-rotor drones in confined, uneven, and diverse tiny regions. In a nutshell, Guardian-Z10 is a low-cost, high-efficiency pesticide sprayer that can easily replace human workers while guaranteeing more pesticide penetration and improved accuracy to lessen pesticide residue. Thanks to its proximity detectors, it is capable of flying independently across uneven terrain. Agras MG-1S, an octocopter with a similar modular design, can spray 6,000 square meters in about 10 minutes with a payload of up to 10 kg of herbicides, insecticides, and fertilizers–a task that is 60 times quicker than hand spraying. MG-1S uses radar-based sensors to autonomously modify its spray depending on flight speed and centimeter-accurate height over crops. There are seven different types of unmanned aerial vehicles (UAVs) classified by size, flying duration, and capabilities, as shown in the classification system for civilian drones in [194].

Because of its controlled environment and low maintenance requirements, it is ideal for greenhouse gardening. According to a thorough spectral analysis, the classification accuracy for irrigation was 96%, for nitrogen it was 83%,

FIGURE 10. Agri-Robots used in smart farming.

and for weed control it was 100%. In addition, hyperspectral data may be processed using the pattern recognition methods of ANN [195] and SVM [196]. The author and coworkers in [197] assessed WSN applications in agriculture and highlighted sensor requirements in 2014. The authors set out to employ networked sensors to develop practical and productive agricultural solutions. WSN was first used in farming by [198].

For research, [199] focused emphasis on soil health monitoring, which provides real-time readings of variables like temperature, soil moisture, pH, and humidity on a farmer's smartphone screen. As an example of progress toward Agricultural 4.0, [200] have addressed in depth how IoT and WSN might be used in precision agriculture. The "Plant Spike" WSN system for soil health monitoring that Yu et al. [201] created is both inexpensive and energy efficient. The Internet of Things was used by [202] to keep tabs on the condition of crops and increase yield. In [203], we develop and test AgriTalk, a low-cost IoT platform, for use in growing turmeric. The macronutrients N (Nitrogen), P (Phosphorus), K (Potassium), pH, soil moisture, and humidity are all monitored by the soil health monitoring system created by Goswami et al. [204] using the IoT. FarmFox, created by the authors of [205], is an IoT-enhanced gadget that can evaluate the detected information and broadcast it to the user through the internet. Using a wide range of agricultural sensors, drones, and IoT hardware and software utilities, the authors of [206] propose a comprehensive smart agriculture application. Additional state-of-the-art works on IoT and WSN for the smart agriculture domain are provided in Table 8.

12) FORECASTING CROP YIELDS WITH TRADITIONAL DATA MINING TECHNIQUES

To predict agricultural yields using Deep Learning, In [221] author conducted a systematic literature review, revealing that neural networks like CNN, LSTM, and DNN are commonly used. Authors compared Deep Learning approaches for apple orchard fruit recognition, finding that techniques like U-Net and CNN performed less effectively than other methods for yield mapping, with gaussian mixture models showing better results. In [222] authors explored Deep Learning techniques for fruit counting and yield estimation, recommending LSTM, deep regression, and CNN detectors. In [223] authors developed a self-predicting platform for agricultural yields based on crop diseases using CNN. In [100], authors assessed Deep Learning applications in dense farm settings, concluding that Deep Learning performs better in such scenarios. Authors reviewed Deep Learning algorithms for crop output and nitrogen status estimation using tabular data. In [224], authors found that hybrid networks and RNN-LSTM networks are best for predicting crop yields using Deep Learning, particularly due to the effectiveness of RNN and LSTM in handling agricultural production time-series data. Despite these studies, a comprehensive review of Deep Learning for agricultural production prediction is lacking in the literature, leaving gaps in technical details, motivations, and challenges. Our SLR aims to address these gaps by providing an in-depth analysis of key characteristics and problems in the use of Deep Learning for agricultural production prediction.

In order to estimate the potential sugar output from IoT farming, the authors of [225] devised an enhanced multilayer perceptron (MLP) method. Experimental results reveal the effectiveness of the proposed MLP algorithm, achieving a remarkable 99% accuracy, 95% precision, 96% recall, a Minimum Mean Absolute Error (MAE) of 0.04%, and a Root Mean Square Error (RMSE) of 0.006%, signifying its potential for precise and efficient prediction in the domain of IoT agriculture. Autor in [226] suggested a classification approach to artificial neural network evaluation of the sugar crystallization syrup process. For the purpose of predicting the inclusion measure function in the Hellenic sugar sector, In [227] author suggested a fuzzy-based technique Hellenic Sugar Industry (HIS). Focusing specifically on grapes as a case study, the article comprehensively examines current applications of machine vision algorithms for ripeness estimation in viticulture. The review delves into the state-of-the-art algorithms, discussing various applications and assessing their limitations, challenges, and future trends. Furthermore, the study investigates the integration of machine vision algorithms with grape harvesting robots, emphasizing the potential for real-time ripeness measurement in the field. A literature for predicting agricultural yields from meteorological characteristics was conducted by [228]. This study explores the integration of computational approaches, particularly machine learning, to address complex agricul-

TABLE 8. Connected and intelligent farming technologies examples using IoT and AI.

Description	Category	Company/Tool and Reference
A ML-based soil-analysis system that gives you an idea of the soil's potential and its limitations	Climate conditions Monitoring	allMETEO [207]
A set of goods that boost productivity by removing manual inspection. They function by deploying a broad variety of sensors producing a report back to an internet dashboard,	Climate conditions Monitoring	Smart Elements [208]
A sensor and accompanying software package that enables constant data collecting and transmission from farm to smartphone.It also has a dashboard where the most up-to-date phenological and disease models may be used to track patterns and evaluate potential threats to agricultural goods.	Climate conditions Monitoring	Pycno [209]
A system for tracking pests and illnesses and compiling data for use in handheld devices. It saves time and effort compared to more conventional techniques (like paper), allowing for a more seamless rollout. The following metrics may be seen in real time thanks to the synchronization of the stored data with the server: Charts and reports on pests and illnesses, as well as a satellite map with recorded points and the farm's current sanitation condition, are also included.	Greenhouse automation	Farmapp [210]
A system that allows for wireless automation and control, data collecting, optimization, monitoring, and visualization by closely integrating hardware and software components.	Greenhouse automation	Growlink [211], [212]
A gadget that takes environmental and plant-related readings and uploads them to the cloud, where they may be accessed from anywhere and at any time. Stress, pests, and disease indicators are provided in real-time.	Crop management	Arable [213]
An online resource for raising productivity levels. As a result, farmers may build on-site monitoring, big data, and advanced analytical solutions for long-term agricultural goods based on accurate, up-to-the-minute information on pests, diseases, and the state of their crops.	Crop management	Semios [214]
An innovative approach to animal monitoring with the primary goal of collecting and analyzing crucial data, down to the individual animal level. When necessary, it provides farmers with information on heat, health, and nutrition that they may use to make informed decisions.	Livestock monitoring and management	SCR/Allflex [215]
A high-tech collar worn around the neck of dairy cows to track their activity, ruminating patterns, and body temperature. The system's intelligent algorithm enables early diagnosis of health problems even before outward symptoms manifest. It can track your every step and analyze your gait to pinpoint. Comfortable for the animal and low-maintenance thanks to its solar-powered base unit and waterproof, non-invasive monitoring system.	Livestock monitoring and management	Cowlar [216], [217]
An algorithm that examines drone and satellite imagery of farmland for telltale signs of pests, illnesses, and inadequate nutrition. In order to optimize farm productivity and examine analytics of on-farm performance, it converts photos into a prescription map. Cloud-based data generated for prescription formulation may be imported into practically all agricultural programs.	Predictive analytics	Farmshots [218], [219]
A system for monitoring the weather and gathering data on the viability of crops. Its purpose is to provide comprehensive data and analysis to aid in making daily and worldwide agriculture choices in real time.	Predictive analytics	aWhere [220]
By keeping tabs on the state of the fields, this method makes it easier to organize and direct harvesting operations. Additionally, it promotes agricultural goods	End-to end farm management systems	FarmLogs [217]

tural challenges like crop improvement, yield prediction, disease analysis, and water stress identification. ML and its uses in agriculture were explored by [229]. The evaluation encompasses crop management, addressing predictions of yield, disease and weed detection, crop quality assessment, and species identification. Additionally, the review extends to livestock management, covering predictions related to animal welfare and production, as well as water and soil management. In [230], the authors conducted a literature review on fruit ripeness determination with the purpose of finding the best time to harvest and predicting production.

13) DEEP LEARNING APPROACHES FOR CROP YIELD PREDICTION

There are a number of AI-based smart solutions for precision agriculture and farming that are now available on the market and summarized in Table 9.

B. MACHINE LEARNING APPLICATIONS IN HARVESTING

When the fruits and vegetables are mature, the most crucial step is harvesting, following the pre-harvesting stage's attention to soil, seeds, weeds, etc. Size, color of the skin, hardness, flavor, quality, market window, maturity, fruit detection, and harvest categorization are all critical characteristics to consider at this stage. Careful and accurate fruit picking is directly proportional to financial gain. According to the findings of the poll, farmers are able to cut down on harvesting losses with the use of auto-harvesting robots, machine learning, and deep learning approaches. Here we show how ML and DL algorithms are used for harvesting. To illustrate the current state of intelligent autonomous harvesting robots in horticulture, author in [231] provided a comprehensive overview of systems for harvesting sweet peppers, tomatoes, apples, and kiwis. Automated harvesting robots boost farmers' bottom lines by cutting down on labor-intensive harvesting times and increasing overall output. A convolutional neural network (CNN) model for on-tree fruit recognition was created [232] using the YOLO technique. The creation of this dataset was accompanied by the addition of both genuine and synthetic photographs of pear and apple trees. We used an open-source labelling program called BBox-Label-program to label the

TABLE 9. Commercially accessible AI-based smart farming tools.

Product	Website	Company
Indoor farming system driven by AI	https://ageyetech.com/	AGEYE Technologies
Predicting the weather, assessing agricultural sustainability, and evaluating farms for the presence of diseases and pests are all possible with the use of satellite data and ML algorithms.	http://www.awhere.com	aWhere
Robotic agricultural machinery that can monitor plant health and prevent weed growth.	https://bluerivertechnology.com	Blue Reiver Technology
Platform that uses satellite and drone imagery to do integrated scouting and provide variable-rate prescriptions to farmers	http:// farmshots.com	FarmShots
Intelligent systems that use cheap sensors to measure key agricultural variables for the average farmer.	https:// fasal.co	Fasal
Vegetable harvesting and packaging robot	https://www.harvestcroorobotics.com	Harvest CROO Robotics
System for controlling irrigation, preventing mildew, and coping with drought based on artificial intelligence-monitored soil moisture levels	https://www.heliopas.com	HelioPas AI
Online software for controlling water sprinklers Ibex	https://hortau.com	Hortau Inc
Farming robots that can do everything from detecting weeds to spraying them down by themselves are becoming a reality.	http://www.ibexautomation.co.uk	Automation
To detect soil flaws and nutrient deficits, a Deep Learning-powered picture recognition program is being developed.	https://plantix.Net	PEAT
Robotic and automated AI methods for greenhouse growers	https://root-ai.com	Root AI
A ML-based soil-analysis system that gives you an idea of the soil's potential and its limitations	https://www.tracegenomics.com	Trace Genomics

photos. The model was trained using over 5,000 photos of apples and pears. We trained the model using the Amazon cloud infrastructure. When it came to detecting fruit on trees, the model was over 90% accurate. In [233] author looked at two different deep neural network models for fruit classification: a tiny CNN model and a VGG-16 fine-tuned model. The second model was a fine-tuned visual geometry group-16 pre-trained DL model, whereas the first one was constructed with six layers. In order to test how well the suggested models worked, two datasets were used. Dataset-2 has 5946 photos spread among 10 classes, whereas dataset-1 is publicly accessible and contains 2633 color images. The assertion was made that the VGG-16 model, after being fine-tuned, attained outstanding accuracy on both datasets. By using a systematic method and analyzing the network's input, In [234] different ways to improve the network's performance on unseen data were investigated. The decision to fuse features was made instead of altering the network design or adding more depth to the neural network. Applying bio-inspired characteristics may simplify models without sacrificing accuracy or generalizability, according to the results. It is said that this method exhibits more encouraging outcomes with the robust DL model in real-world applications for color-centric data classes. In August and September of 2018, the author collected 6189 photographs for the project and annotated 150 of them by hand. A machine vision method was suggested by [235] to classify date fruit pictures according to various stages of ripeness, which aids in the decision-making process about harvesting. A total of 8072 photos were compiled from five distinct date kinds, each with its own unique pre-maturity and maturity stage: Naboot Saif, Khalas, Barhi, Meneifi, and Sullaj. Few obstructed photographs were among the many obtained from a variety of angles, sizes, and lighting conditions. Using two well-known convolutional neural network (CNN) models for input transfer The three classification models that were built to categorize date fruit based on their harvestability, kind, and maturity stage were constructed using AlexNet and VGGNet. With a speed of 20.6 ms and an accuracy of 99.01%, the VGG-16 model proved to be the winner. To quantify yield-related phenotypes from ultra-large aerial data, Bauer et al. [236] created a platform called AirSurf. This platform links up-to-date ML approaches, current computer vision, and integrated software engineering standards. In the time leading up to harvest, the author asserts that this platform helps to raise crop production and marketability. Using a cheap gripper and a machine learning approach to determine the cutting spot, Zhang et al. [237] created a harvesting robot for autonomous harvesting. An automated harvester system that can safely harvest crops with peduncles was the focus of the research. Robot arms equipped with Single Shot MultiBox Detectors (SSDs) and stereo cameras were suggested by Onishi et al. [238] for autonomous fruit identification and harvesting. An apple tee named "Fuji" was used to test the system. By rotating the hand axis, the robotic arm can identify the location of harvestable fruit and retrieve it. The system detected 90% of the fruits and harvested them in approximately 16 seconds, according to the trial results. For precise fruit counting from picture order, Liu et al. [239] suggested a new pipeline that combines segmentation, 3D localisation, and frame-to-frame tracking. The datasets consisting of oranges and apples were used to test this model. The detailed description of harvesting strategies was reported in Table 10.

TABLE 10. Detailed description of harvesting strategies.

Sr. No.	Features	Targeted Fruits	Dataset Used		No. of Samples trained	Best Model	Accuracy	Reference
			Public	Own				
1	Real-time fruit shape, color and other attributes detection	Apple and pear		P	4950	YOLO	90.01%	[234]
2	Different fruits classification	Different fruits	P	P	8600	VGG-16	99.76%	[235]
3	Bio-inspired outdoor fruit detection	Strawberry		P	4219	-	66%	[236]
4	Local and spatial features and pattern detection for dates	Dates		P	8000	VGG-16	99%	[237]
5	Fruit harvesting robot	Apple	P		169	YOLO	91%	[238]

TABLE 11. Detailed overview of Post-Harvest operations.

Sr. No.	Features	Targeted Fruits	Dataset Used		No. of Samples trained	Best Model	Accuracy	Reference
			Public	Own				
1	Post-Harvesting Bananas grading and classification	Banana		P	1115	Tensorflow and OpenCV	90%	[244]
2	Tomatoes grading and disease classification	Tomatoes		P	8100	SVM, ANN	97%	[245]
3	Post-Harvesting Bananas classification	Banana		P	1165	SVM, ANN	94%	[246]
4	Auto Apple-sorting	Apple		P	185	K-mean, Decision Tree	80%	[247]
5	Dates grading	Dates		P	1865	BPNN	80%	[248]

C. MACHINE LEARNING APPLICATIONS IN POST-HARVESTING

Finally, and most importantly, agriculture has to pay greater attention to post-harvesting. Negligence in the post-harvest phase may ruin all the hard work farmers put into estimating yields and harvesting their crops, leading to a devastating financial loss. When it comes to fruit grading, every nation has its own set of norms and regulations. A document outlining the steps to take in order to ensure the quality and safety of mangoes after harvest was published in [240]. For everyone involved in the horticulture supply chain, this is quite illuminating. Researchers found that improper post-harvest handling techniques may reduce fruit quality and quantity, leading to higher losses overall. Decay alone was responsible for 31% of the losses recorded at the retail level. Inadequate harvesting, negligent handling, and unsuitable packing and transportation all contribute to losses. Low quality due to high levels of pre-harvest infections is the result of ineffective disease control throughout production. A lot of deterioration, such anthracnose and stem end rot, is visible. A training handbook for "handling fresh fruits, vegetables and root crops" was provided to the Grenada government and the FAO as part of the "Agricultural Marketing Improvement" Project TCP/GRN/2901 in [241]. Through the implementation of a systematic agricultural marketing system, this initiative aimed to enhance the profitability of horticultural goods and root crop producers. With the goal of reducing losses across the board, this publication examines each step of the post-harvest process in great depth. Using a deep learning system and image processing, [242] investigated how to evaluate Cavendish bananas. Class A big-hand, Class B small-hand, and Cluster class (part of hand) bananas were the end result of a model construction process including Python, OpenCV, and Tensorflow. The model's categorization accuracy was above 90%, according to the results. To grade tomatoes after they are harvested, [243] suggested a method that uses machine vision. The system is designed to process RGB pictures that are sent into it. The tomato photos were carefully labelled into four categories: defect, healthy, ripeness, and dataset. A total of fifteen criteria were evaluated in making the choice to put the images into one of four categories based on matching attributes. With a detection accuracy of 0.9709, RBF-SVM outperformed the competition in category 1, which includes healthy and defective items. A method for banana (Musa acuminata AA Group 'Lakatan') categorization using ML approaches based on tier-based was developed by [244]. In this investigation, a tier-based method that does not involve intrusive procedures was used. The bananas were sorted into four classes: additional, class I, class II, and rejected using ANN, SVM, and RF classifiers. With a 94.2% accuracy rate, the random-forest method proved to be the best of its kind. Early detection of bruising in 'Pinggu' peaches was investigated and contrasted using two hyper-spectral imaging technologies: long-wave near infrared (LW-NIR) and short-wave near infrared (SW-NIR) [245]. Utilizing multispectral PC pictures, this work developed and evaluated an enhanced watershed segmentation technique that relies on morphological gradient reconstruction and marker extraction. A suggested algorithm correctly identified 97.5% of healthy peaches and 96.5% of damaged ones, according to the results of the experiments. Using quality inspection and automated real-time grading, [246] created a method for apple fruit. An enclosed cabin with a camera, load cell, and control panel units is part of the designed system, which also includes a roller, transporter, and class conveyors. In addition to sorting apples into several categories according to size, color, and weight, the system can also detect spoiled fruit. Capturing and processing the apple picture only took 0.52 seconds using the suggested approach. The machine sorted an average of fifteen apples per second. The author claims that the algorithm can sort various fruits, such as potatoes, with an average accuracy ranging from 73% to 96%. Ohali created a date fruit grading and sorting system using machine vision [247]. Based on the RGB picture input, the system could determine whether the dates were of grade 1, 2, or 3. The research demonstrated an 80% success rate using a back-propagation technique. Considerations such as size, shape, texture, color, and flaws determine the quality of fruits and vegetables. To sort products by quality metrics, one must use a number of techniques, including data collecting, pre-processing, picture segmentation, feature extraction, and classification. In their comprehensive review, [248] compared the algorithms employed at each step of the quality inspection process for fruits and vegetables. To address the issue of incorrect fruit categorization, [249] introduced a novel framework named "MNet: Merged Nett." With 12,000 photos divided into six categories, the author has assembled his own dataset of the best Indian fruits. The detailed overview of post-harvest operations was reported in Table 11.

IV. EMERGING FRONTIERS FOR DATA MINING IN AGRICULTURAL INNOVATION

Data collection, analysis, and application for agricultural efficiency face a broad variety of difficulties. For farmers to succeed in the modern digital era, protecting personal information and confidential data is a crucial challenge. It's not uncommon for agricultural information systems to have issues with data availability and quality. This becomes much more difficult when more data becomes available in real time. It is not easy to mine data efficiently, and it might be more trickier to integrate spatial and semantic meaning.

A. CHALLENGES

Agriculture is a big arena for the use of machine learning and deep learning, and it presents a number of difficulties. Some possible Challenges are indicated as follows:

1) PRIVACY

Agricultural data includes their contact details. Most farmers whose data is made public through digital platforms won't have a clue as to what that data says about them. It's true that farmers have no idea their data is being collected, much less how it's being put to use. Organizations may use data mining to acquire massive quantities of information on farmers, which might be used to paint a detailed psychological or personality image of them. The information, even if not utilized maliciously, might nonetheless damage his reputation if it were to become public knowledge or fall into the wrong hands. As a result, he may find it challenging to engage in his regular activities. They need reassurance that their information will only be utilized for research and innovation, and not to gain an unfair advantage. The privacy of farmers' information may be compromised by data mining. It takes a lot of effort and money to adopt privacy and confidentiality rules.

2) DATASET AVAILABILITY AND THE SIZE ISSUES

Infection photos of specific leaves on plants are difficult to obtain by. As a result, the current plant databases are quite limited in scope. For academic reasons, thousands of photos have been reported on only in a few of papers. Even more so, the photographs in the database were gathered under very restricted settings. We think it's important to collect photographs in natural settings so the algorithms can be more useful in everyday life. The time has come for quick and easy picture collection of leaves. Such databases would be much appreciated by the scientific community if the photographs were recorded in real time. The results of this poll show that many academics rely on external data repositories like Kaggle, Meandly, IEEE Dataport, etc. for conducting their studies. If necessary, data is lacking, researchers will have to assemble their own.

3) DATA INTEGRITY AND ACCURACY

To be successful in agriculture, we need to collect and analyze a great deal of data. The sheer volume of this new data has rendered traditional methods of analysis ineffective. The use of data mining analysis will significantly improve crop management. In order to glean useful insights from the DM procedure, high-quality data is required. Agricultural data is often disorganized and incomplete since it was compiled from a wide variety of sources, such as databases and models. There are gaps in and many inaccuracies in the data obtained from these sources. In data mining, a lot of groundwork must be done first, before any analysis can be done. In order to provide models with accurate information, researchers must first do data processing (geographical and temporal) to remove the effects of problems like ambiguity, persistence, and incapability (geographical and temporal). Additional data use is inevitable. The uniformity of syntax and semantics is therefore required to guarantee the portability of data in an environment. All kinds of novel analyses and products may be made possible by better data management. Data transport reliability is a major issue for IoT devices. In order for devices to gather and transmit reliable data, it is essential that they be able to verify its accuracy. If a false reading is taken, system reliability will suffer greatly.

4) CROP DATA CLARITY AND NOISE

To extract the contaminated part of a picture, image segmentation is used. A contaminated leaf segment is more difficult to isolate from a picture when the backdrop contains elements other than white and black, such as plants, leaves, dirt, grass, and so on. Photos taken in the field for the purpose of diagnosing crop diseases in real time may include a lot of distractions, especially if farmers wish to get an accurate representation of the scene. Therefore, the system has to be able to filter out any unnecessary details in the picture, leaving behind just the targeted area.

5) IMAGE CONDITIONS

All publicly accessible datasets include photos captured in well-regulated laboratory settings or created using animation methods. Consider the results that would occur if a farmer or capturing device in the field attempted to capture the same object at various times of day. It's tough to get a comparable shot in that situation because to all the elements at play, such as the varying levels of light and moisture. Therefore, it is necessary to take pictures of the same leaf from different angles, at different times of day, and in different weather conditions.

6) LIMITATIONS AND CONCERNS IN EXISTING FEATURE EXTRACTION METHODS

Important building blocks for every machine learning-based system include preprocessing, feature extraction, and segmentation. In order to choose the most effective preprocessing and segmentation approach, it is important to consider the method of data collecting. It is common practice to use the acquisition method that is most optimal for a given task. There is a wide range of methods released so far for various modules, and this is something we have seen.

7) CLASSIFICATION MODULE PROBLEMS

The identification and automation of plant diseases has been a hot area of study for quite some time. Despite employing few images for training and testing, researchers claim to have achieved extremely acceptable outcomes. Diverse classifiers are being investigated by researchers in this area. The results show that backpropagation neural networks, SVM, and discriminant analysis (particularly linear) are the most effective methods. After that, Nave Bayes, random forest, closest neighbor, and multilayer perceptron are utilized. Results were previously considered to be state-of-the-art, however recent research has shown that optimized deep neural networks can greatly improve on this. Results for large data sets may be enhanced with the help of deep convolutional neural networks if they are employed properly.

8) CONCERNS ON DEVICES

Assuring that technology may be utilized in a broad variety of contexts requires standardization of devices. There are no universally accepted formats for data processing, though. The misinterpreted code might lead to several effects. System, application, equipment, and product interoperability issues may be mitigated with the aid of machine standardization. Communication speeds between devices and servers are now 100 times quicker thanks to advancements in the 5G network. Since 5G can transmit far more data, it is a viable technology for transmitting data from distant sensors. Therefore, 5G must be implemented as a new communication network to accommodate customers' growing need for higher levels of privacy and speedier data transfers. Lack of interoperability is one of the biggest problems.

9) SPATIAL DATA IMPORTANCE

SA's overarching objective is to minimize negative effects on the environment while maximizing financial gain. Standard data mining methods, which were built for use with relational databases, have limitations when applied to data that is physically spread out. Smart farming necessitates the development of novel data mining techniques that account for geographical and temporal relationships.

10) INCORPORATION OF AGRICULTURAL DOMAIN KNOWLEDGE IN DATA MINING

Agronomy, soil science, environmental studies, and other related fields are all part of agriculture's broad multidisciplinary scope. In data mining, we may leverage information from a wide range of resources. There are additional difficulties to overcome because of sensors and large amounts of data, in particular the problem of operable semantics, or how to encode data such that it retains its meaning across time. One of the toughest challenges in data mining is the issue of integrating domain knowledge. This approach may be seen as a sort of agricultural fusion since it bridges the gap between agricultural domain knowledge and data mining study.

11) DRONES

The flight route must account for the overlap between flight lines since the drone can only stay in the air for an hour at a time. Most drones are out of most people's price range, but the ones with the best cameras, sensors, and other hardware and software are in a league of their own. In many countries, using a drone without the proper licensing and at a height of less than 400 feet is illegal. Drone use is influenced by the weather. It is important to consider the meteorological conditions, such as wind speed and precipitation, before flying a drone. Some supplementary difficulties are worth keeping in mind:

1) First, there is a need figure out what the issue is and what the market needs.
2) Getting a deep insight into customer behavior and tech use.
3) Simple and straightforward Application.
4) How well the model works in practice.
5) Battery life and power requirements for the product to operate.
6) Different ways in which cameras may be set up by the end user to use with computer vision models.

Some suggestions for improving the effectiveness, precision, smoothness, and deploy ability of the implementation process have been compiled based on the findings of this extensive research:

1) Target a narrow ML task like classification or recommendation as your primary goal.
2) Make your own data set for use in training the model, and then share it with the research community using open channels like Kaggle, Meandly, IEEE Dataport, and so on.
3) Test and validate your models using data that is already accessible to the public.
4) In order to reduce the length of time needed to train a model, ''Transfer Learning'' techniques may be used.
5) AutoML is a state-of-the-art approach to rapidly developing high-quality machine learning models.
6) To best help the target audience, the model should be integrated into a running application.

B. POTENTIAL FUTURE SCOPE

In the following paragraphs, we'll go through a few potentials that might advance the state-of-the-art smart farming and provide scientists new directions to explore:

- Disease stage determination is a crucial part of plant disease diagnosis. The ability to predict the spread of diseases will let farmers take preventative measures and mitigate losses.
- Farmers often resort to chemical treatments for illnesses without doing proper research or statistical analysis. This kind of action is very harmful to people's wellbeing. Whether or not certain chemicals are needed may be determined with the use of a powerful picture processing application, the development of which will be facilitated by such an application.
- In the medical literature, many methods have been proposed for illness detection. However, these applications only work with images that have a solid, black backdrop. That's why it's so important to have access to internet tools and mobile applications for diagnosing plant diseases. Technology like these will help farmers pinpoint the source of a disease. Using this kind of program, analysis reports may be compiled and sent off to a disease specialist for further guidance.
- We recommend transfer learning as a viable option due to the complexity of the data, especially during the training phase. Some potential areas of investigation for autonomous plant disease diagnosis include long short-term memory, optical flow frames, temporal pooling, and 3D convolution. Finally, improved and more carefully crafted procedures are needed for future studies in this field.
- There is a lot of promise for the Internet of Things to improve agri-food supply chain traceability. Meanwhile, LoRa, ZigBee, and WiFi are the most often utilized IoT communication technologies in these publications and new high-speed communication technologies like 5G and NB-IoT are anticipated to be extensively employed to improve the modernization and intelligence of agricultural output. There is a great deal of space for innovation in agriculture that is based on the IOT as existing technology continues to progress.

V. CONCLUSION

In conclusion, the integration of agricultural technology, especially through data-driven solutions and machine learning, presents a promising trajectory for the agricultural sector. The adoption of artificial intelligence-based applications, such as GPS-guided automatic irrigation and autonomous robots for weed control, offers avenues to improve resource efficiency while reducing reliance on harmful pesticides. Unmanned aerial vehicles for crop monitoring and pest management usher in transformative approaches to farming practices. Through the application of machine learning and deep learning, advancements in plant disease detection, water conservation, pesticide management, phenotyping, and overall yield improvement are realized. Accurate disease diagnosis becomes pivotal in safeguarding agricultural productivity, addressing long-term challenges like climate change, and mitigating food shortages. The use of image recognition software and pretrained models from extensive datasets, such as PlantVillage and ImageNet, demonstrates remarkable accuracy in detecting plant diseases, potentially revolutionizing disease management. Embracing these technological solutions, coupled with ongoing research and dataset refinement, undoubtedly empowers the agricultural sector to confront growing challenges and seize opportunities for a more efficient and environmentally responsible future.

However, it is essential to consider certain limiting circumstances in the widespread implementation of these technologies. Issues such as high initial costs, the digital divide in rural areas, and concerns about data privacy and ownership pose challenges to the equitable adoption of advanced agricultural technologies. Additionally, the reliance on machine learning models is contingent upon the availability and quality of data, necessitating ongoing efforts in data collection and curation. Looking ahead, future theoretical and applied implications suggest the need for continued research and development to refine existing technologies and explore novel solutions. Collaborative efforts between technologists, researchers, policymakers, and farmers are crucial to ensure that these innovations are accessible, practical, and tailored to diverse agricultural landscapes. Furthermore, considerations for the ethical use of AI in agriculture, including transparency, accountability, and addressing potential biases in algorithms, will be paramount for the responsible deployment of these technologies.

VI. NOMENCLATURE

Abbreviation	Full Form
ICT	Information and Communications Technology.

GDP	Gross Domestic Product.
IoT	Internet of Things.
ML	Machine Learning.
AI	Artificial Intelligence.
UAVs	Unmanned Aerial Vehicles.
SA	Smart Agriculture.
PF	Precision Farming.
AutoML	Automated Machine Learning.
IPv6	Internet Protocol Version 6.
DL	Deep Learning.
DSS	Decision Support System.
GPS	Global Positioning System.
NN	Neural Network.
CNN	Convolutional NN.
GLCM	Grey-Level Co-occurrence Matrix.
KNN	K-Nearest Neighbors classifier.
DT	Decision Tree.
NB	Naive Bayes.
RF	Random Forest.
SVM	Support Vector Machine.
SGD	Stochastic Gradient Descent.
PD	Plant Disease.
PLDD	Plant Leaf Disease Detection.
CNN-LSTM	Convolutional Neural Network - Long Short-Term Memory.
PM	Powdery Mildew.
CA	Classification Accuracy.
UAV	Unmanned Aerial Vehicle.
WSN	Wireless Sensor Network.
MLP	Multilayer Perceptron.
HIS	Fuzzy-based technique (not explicitly defined).
CV	Computer Vision.
DL	Deep Learning.
GPS	Global Positioning System.
SVM	Support Vector Machine.
NB-IoT	Narrowband Internet of Things.
LoRa	Long Range.
DM	Data Mining.

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