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REVIEW ARTICLE

Machine Learning for Smart Agriculture and Precision Farming: Towards Making the Fields Talk

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Abstract
In almost every sector, data-driven business, the digitization of the data has generated a data tsunami. In addition, man-to-machine digital data handling has magnified the information wave by a large magnitude. There has been a pronounced increase in digital applications in agricultural management, which has impinged on information and communication technology (ICT) to provide benefits for both producers and consumers as well as leading to technological solutions being pushed into a rural setting. This paper showcases the potential ICT technologies in traditional agriculture, as well as the issues to be encountered when they are applied to farming practices. The challenges of robotics, IoT devices, and machine learning, as well as the roles of machine learning, artificial intelligence, and sensors used in agriculture, are all described in detail. In addition, drones are under consideration for conducting crop surveillance as well as for managing crop yield optimization. Additionally, whenever appropriate, global and state-of-the-art IoT-based farming systems and platforms are mentioned. We perform a detailed study of the recent literature in each field of our work. From this extensive review, we conclude that the current and future trends of artificial intelligence (AI) and identify current and upcoming research challenges on AI in agriculture.

1 Introduction to Smart Agriculture

Agriculture is the principal source of food supply and gross domestic product (GDP), as it accounts for 6.4% of the entire global GDP. Agriculture is at least a significant source of business in nine countries on the globe. Agriculture provides fuel as well as jobs for millions of people [1]. The Food and Agriculture Organization of the United Nations (FAO) claims that global food demand must grow to 70% by 2050 to meet increased population needs [2]. At the moment, enough food is produced to feed everyone on the planet, but still, 500 million people suffer from malnutrition, and over 821 million go hungry. About two-thirds of the world's population will live in cities in next coming decades. An increase of over half of this total global population will be in the countries in Africa, Indonesia, Pakistan, the Democratic Republic of Congo, India, Indonesia, Egypt, the United States, and Tanzania. 473 million people are expected to join the middle class in India and Nigeria by that year [1]. A rapid increase in the number of people in this population represents a challenge to attain the target of eliminating hunger laid out in the text Sustainable Development Goals (SDGs); it may be difficult to meet 40% of water needs by 2030; over the same time period, 20% of cropland may become degraded. Because food production requires more resources than the available supply will allow, farmers must use more sustainable methods to increase production and conserve resources [3].

The world must increase its annual cereal production by 3 billion tons and meat production by more than 200%

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by the year 2050 to supply the global population's needs. The cereal will be provided by yield increases in production [4]. An increase in crop size and farm structure is required as well as an up-to-date approach to technologies. Although this might be possible, it is still unclear if it can be done in a sustainable manner and inclusive manner. However, there is a significant and rapid transformation required to reengineer the farm operations at tremendous scale and speed. Agricultural industries are interested in implementing new technology for getting more out of each harvest because of unpredictable weather, increasing demand for food, and rapid growth in the population [5]. More and more uses are being found for artificial intelligence (AI) in agriculture as it develops. At the same time, the Internet of Things (IoT) and the Fourth Industrial Revolution (Industry 4.0) allow for new technologies and innovations to be generated. The modern agricultural technologies and innovations are known as "smart agriculture," or "Agriculture 4.0," can help crop production while also reducing water and energy use [6]. Through the integration of environmental measurements, prediction technologies, these will be possible. As new capabilities have been created by smart farming, agricultural processes can be optimized to allow greater productivity and fewer natural resources to be used. Smart farming uses diverse technologies and platforms to enable farmers to leverage new ideas [6].

The "digital agricultural revolution" in agriculture will transform the systems and help increase efficiency, sustainability, inclusiveness, and transparency. Nonetheless, technologies must be integrated into the agricultural sector on a larger scale to take advantage of their more excellent capabilities. Due to these factors, such as compatibility, heterogeneity, the handling of large amounts of information, and the processing of massive amounts of data, however, numerous security issues remain to be addressed in Agriculture 4.0. Agriculture 4.0 needs to generate, transfer and process data correctly and protect against attacks [7]. Without careful management of data integrity, data-related technologies, such as analytics and smart systems, can't function properly. The system can become inoperable if there is faulty hardware or when used in conjunction with other attacks, putting the security of the whole network and all connected devices at risk. When diverse resources are included, security risks arise, such as loss of privacy, maintaining trust, and making sure the resource is there in the first place. Because the internet of things, cellular, and wireless technologies are inextricably intertwined, it's possible that it will solve many of the new and existing threats to our modern society's agriculture. It must address issues of new to date integrity, date accuracy, and device security, as well as specific security elements, like encryption, data accuracy, and availability [8].

1.1 Smart Farming and Precision Agriculture: A Definition

Farm smart devices are exposed to climate changes (sunlight, rain, hail), engines (used in agriculture), animals, passing through, and people. The above elements allow our farm's smartness to be exposed to vulnerabilities that have not yet been explored elsewhere. One prominent example of the creative use of artificial intelligence in agriculture is the insertion of sensors and actuators in open spaces where external agents, like humans or machinery, could potentially interact with the surrounding environment. If an agent accidentally removes the sensor from the original location or damages it, these controls will lose their functionality. More often than not, the external agents are able to circumvent these devices when they aren't physically tethered, for example, in smart cities. The lack of protection presents a distinct vulnerability in agricultural systems. Larger-scale applications of machine learning in farming are just being worked out. With time, magical results will be achievable for all stages of agricultural research and development.

> As quoted by Allan Savory, "Agriculture is the foundation of civilization and any stable economy".

Precision agriculture (PA) became a prominent component of the third wave of the modern agricultural revolution in the 1980s. PA was first used to focus the application of fertilizers to specific soil conditions. Since then, PA has been used to construct automated guidance systems for agricultural vehicles and tools, autonomous machines and processes, farm research, and agricultural production system management. In agriculture, the fundamental principle of AI automated machine learning (AutoML) is its adaptability, speed, precision, and cost-effectiveness. Artificial intelligence in Agriculture not only assists farmers in the use of their farming abilities but also moves to directed farming to achieve larger yields and better quality with fewer resources. Smart agriculture attempts to reduce farmers' workloads while increasing farm output by incorporating modern technologies such as sensors and actuator networks, unmanned aircraft systems (UAS), satellite imagery, IoT, and drones, and so on [9]. Smart agriculture is a crop management idea that lets farmers to handle geographical and temporal variability in agriculture, such as water management, production management, and fertilizer management, as well as intrusion attacks and real-time data monitoring. Modern agricultural operations frequently employ chemical, pH, wind, rain, temperature, moisture, and auditory sensors. Each sensor has its own set of capabilities and hardware requirements, which are tailored to the conditions in each location. IoT peripherals, image processing systems, big data capabilities, data analytics, and wireless technologies contribute to the development of smart agriculture management.

Smart and precision agriculture has an essential role to play in all aspects of agriculture. That's the coming together of the internet of things (IoT) and information technology (IT). They want to collect data from diverse sources to try to figure out, predetermine, and organize farm activity with regard to their environments. Sensors have become ubiquitous to collect disparate sets of data (soil temperature, moisture, foliage, sunlight levels, and direction). Smart agriculture (SA) is grounded on the combination of digital automation, data collection, data transmission, decision-making, data processing, and data analysis. A sensor network is among the most common data collection and communication technologies in this sector. In smart agriculture, data from the environment plays a critical role [9]. As the soil is a big factor in climatic disease forecasting, meteorological information can alert farmers of infection outbreaks. Increased yield and lower environmental impact are both possible with increased use of the data collected for crop protection. Human has limited capacity to process this data, so they must be made easier with the help of tools and techniques that facilitate analysis to benefit decision-making [10]. The use of data mining techniques is vital in analyzing data. Big data includes patterns, so using different ways of looking at the data is critical in order to discover these patterns. Data mining techniques have been applied to a number of other tasks in the agricultural sector, including the identification of pests, disease detection, and the prediction of yield, and the planning of fertilizer and pesticide use, to date, for example. They are also used for crop management, but other than that, they can explore other models that can assist in measuring the organization of farms. Therefore, collecting this data is such a new input that can directly affect agricultural efficiency, thus providing better results [11]. Figure 1 presents an overall general framework of the applications of the ICT in agriculture domains.

The integration of information and communication technologies in agriculture is known as smart farming. It allows for the use of data collection and analysis in work processes that use ICT to be utilized. European Union (EU) believes that the best technologies and techniques to be the ones that can be fully utilized are satellite imagery, robotics for data collection, and UAVs [12]. A sustainable digital future for European agriculture and rural areas was agreed upon in the EU cooperation declaration of April 2019 on "Information technology for European agriculture and rural areas" by 24 EU countries. Where connectivity is the biggest problem, that is, in rural areas, digital inclusion is the first obstacle that must be solved, according to the SF official declaration. This is quite exciting about 5G as it is expected to improve these scenarios in rural and low-income regions across the EU, but we should be wary of these projections because of their inconsistency [13]. At the end of 2017, Europe's first half-century of IPv6 deployment, only 25 to 53% of rural regions are covered by Next Generation Access Networks [14]. Digitization of agriculture now appears to be a staggering number of initiatives. A recent EU-funded thematic network, known as Smart AKIS, aims to close the knowledge gap in order to generate practical solutions. Even so, the purpose of SF should not only be to make the whole agricultural process more industrial but should also serve the needs of farmers.

Today, we see new methods for agricultural practices, as well as business models, taking advantage of

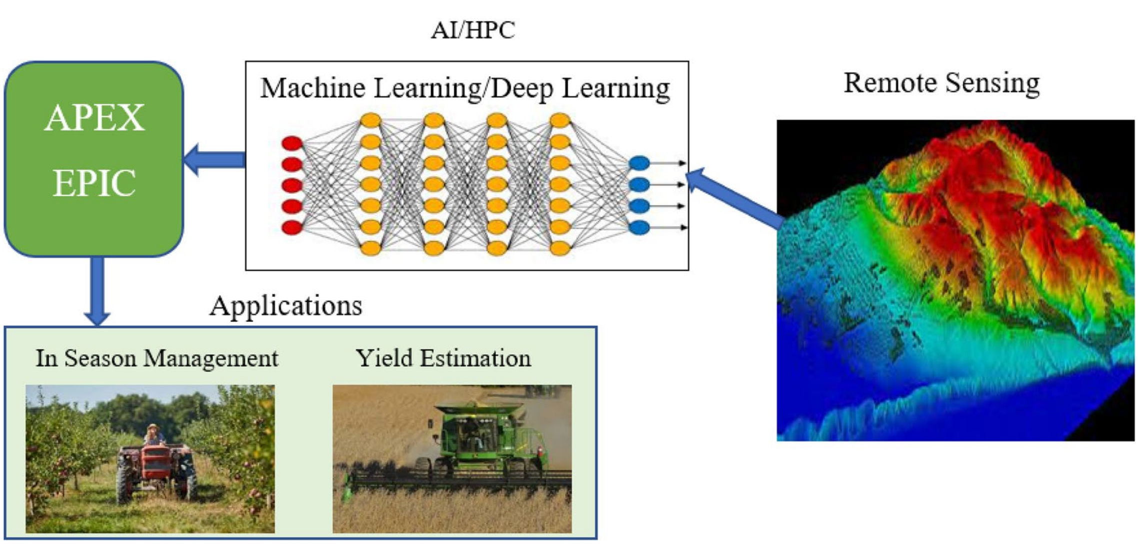

Fig. 1 An ICT framework in transforming traditional agriculture to smart agricultural practices

technological innovations faster than ever before [15]. Another benefit of rental programs for farming equipment, like Trringo in India, includes reduced costs for farmers and support systems that mechanize processes. Such an initiative may be viewed as promoting SF adoption in low-income communities. A French firm is attempting to combine both web-based and hardware technologies to make legacy infrastructure flexible and usable. To meet farmers' needs, Karnott Systems sells a control unit that can be installed on agricultural machinery, combines collecting and exchanging real-time data and geofencing capabilities, and also offers geographic information. Data can be shared via an online service like the API-platform agro's for getting information. Data is available to various farms, providing a valuable research library [15]. Tarris offers an aerial and satellite image in order to support precision farming (PF) using artificial intelligence (AI) as a supporting platform. AgriOpenData provides a Decision Support System (DSS), taking advantage of blockchain, and supports additional services. Robotic agriculture offers a comprehensive solution to the whole plant life cycle from seeding to harvesting with reduced water consumption. With digital ledgers, traceability is, at last, is experiencing a revolution. No matter what level of science fiction you might choose to bring it under, the origin and quality of agricultural products are still significant issues that must be considered. Carrefour, a French multinational retailing company, is interested in using blockchain to help shoppers and industry participants believe in the legitimacy of their transactions. Hectare Agritech use blockchain in their farm trading platform highlights the capacity to take different approaches in different use cases.

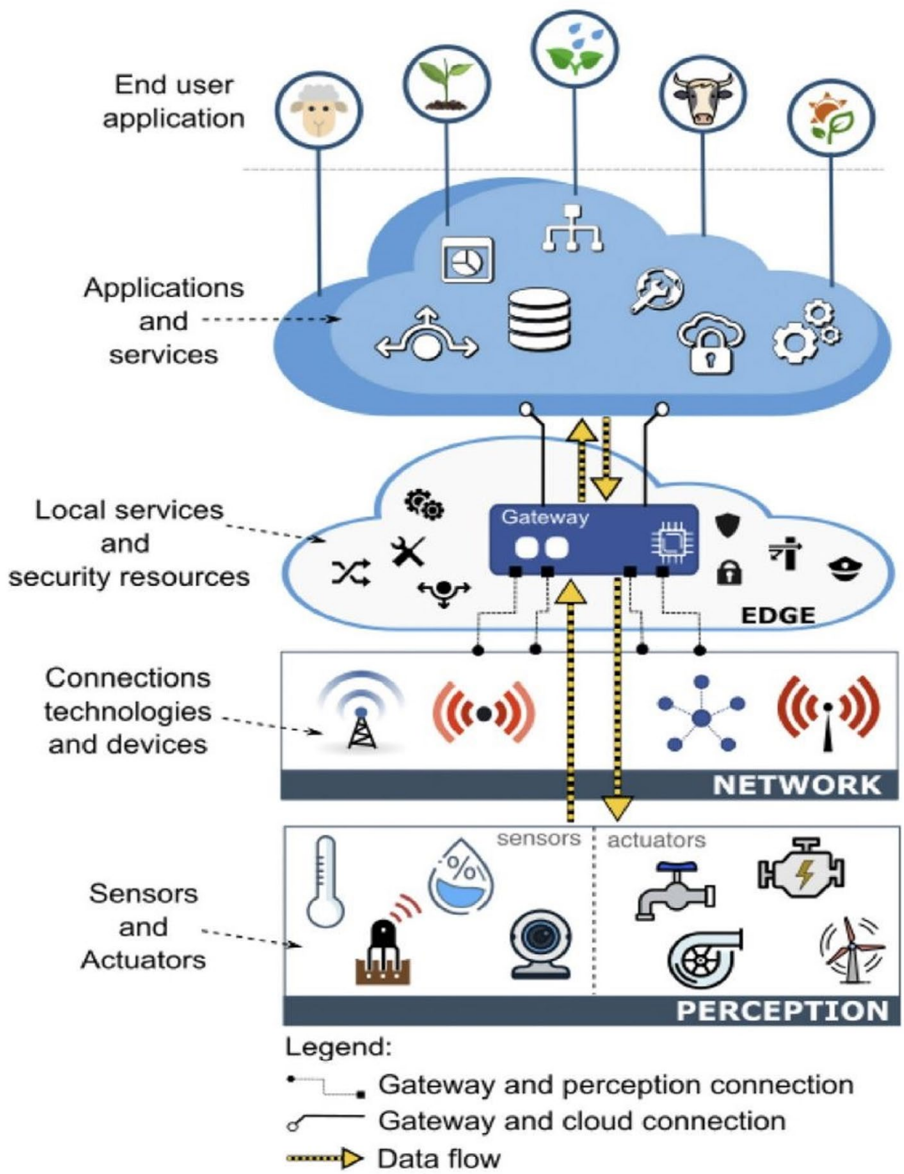

Fig. 2 Structure of smart agriculture components [17]

The system of smart agriculture is illustrated in the graphic form in Fig. 2. It consists of a perceptual device, network functions, and capabilities available at the edge, all wrapped in cloud-based services [16]. For these types of applications, data is gathered and used in the perception layer; sensors, GPS, RFID tags, and cameras may be placed on the farm. Because of this, they cannot process or store information close to the client or perform in the cloud, and they cannot utilize these devices. This component is linked to internal sensor networks via networking technologies, so it can be used with the wireless sensor network (WSN). Security features, data filters, intelligence, diversified processing, multiple in/outbound interfaces, and the gateway may all be located on the creative edge. The edge adds one or more resources, depending on the appliance's features. While some devices only support data returns, others are capable of much more complicated tasks. One of the strengths of programmable gateways is their ability to process data, make decisions, send commands to devices, and send data to the cloud. When you make a connection to the Internet through an Internet Service Provider (ISP), the gateway connects to the cloud; it is helpful for storing and delivering data to customers. Although a large amount of data produced by perception devices will soon be encountered in the big data world, processing in the cloud is costly [17]. For several proposed solutions, cloud computing, bandwidth, and investment costs are immense. Using a heavy gateway with part of the processing on the edges can be advantageous. Moving subsystems to the outer reaches of the farm could decrease its financial expenses. Data downloaded or processed at the edge minimizes network bandwidth, protects and preserves battery life, as well. Thus, the cloud storage of large amounts of data and continual process and decision making allows decisions with users to interact. Processing big data may necessitate the use of high-tech artificial intelligence and pattern recognition tools.

1.2 Need for Automated and Smart Farming

By 2050, the world's population is expected to reach nine billion people. The UN International Food and Agriculture Organization (FAO) estimates that the food supply needed by the people of the world in the year 2050 is about 70% greater than today [18]. For those reasons, climate change will significantly threaten the productivity of food, livestock, and the economic viability of rural communities in the United States, according to the 2018 National Climate Assessment by the U.S. Global Change Research Program. On the majority of U.S. crops, yields will decline as a result of hotter and dryer weather, soil erosion, disease, and pest pressure, and outbreak, especially in the region of these issues while they remain high. As the country's agricultural land usage has led to the destruction of numerous ecosystems, including the prairies of North America and the Atlantic Forest of Brazil [19]. As seen in Fig. 3, there are around 500 billion hectares of agricultural land today; about 40% of the total land on Earth is used for farming [20].

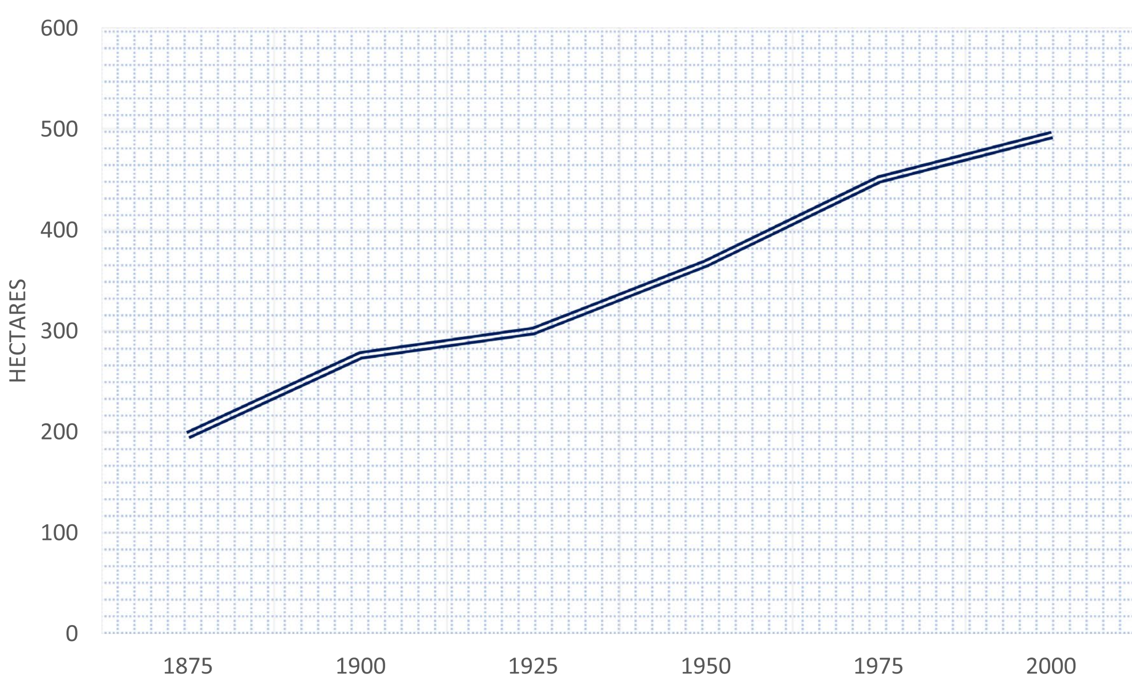

Fig. 3 Total agricultural area over the long-term in hectares [20]

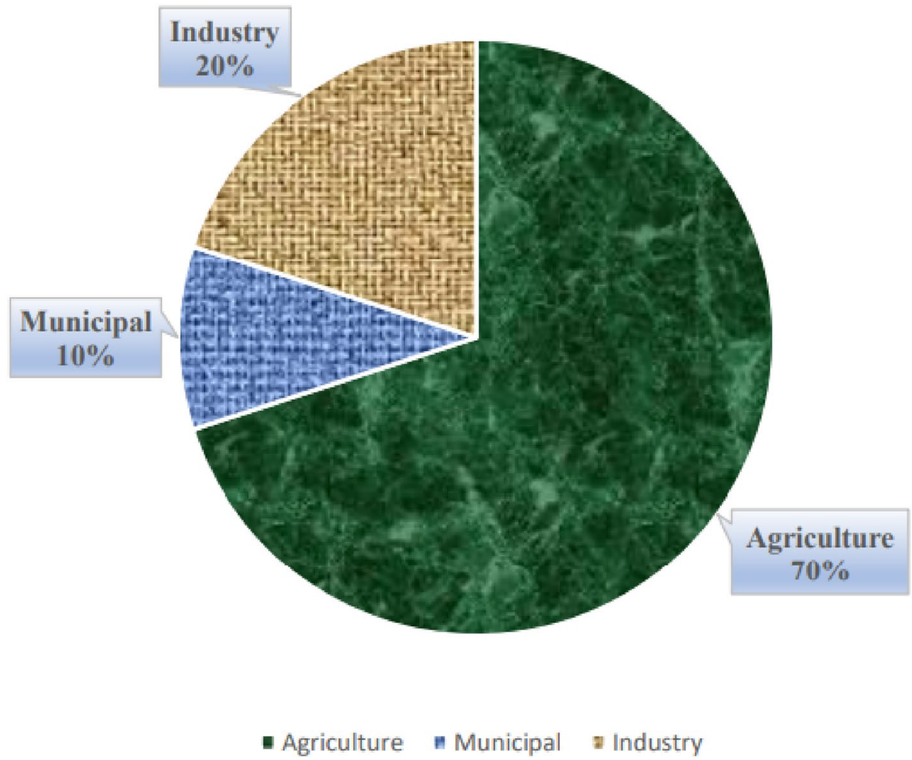

Fig. 4 Water withdrawals by sector [21]

Agriculture accounts for over the course of the past 70% of the global water use, as shown in Fig. 4 [21]. Since agricultural land has expanded so much, global water withdrawals have almost quintupled from 500 to 2500 cubic kilometers. Population growth, as well as climate change, have made increasing food production a serious problem. It is apparent that the agriculture industry must alter current approaches to production and adoption to favor land and water use practices while also avoiding the threat of volatile markets. The use of several new information technologies allows the agriculture industry to enter into a data-driven era.

India is an agrarian country, with agriculture accounting for 16% of India's GDP and 10% of overall exports, respectively. Approximately 75% of India's population is dependent on agriculture, either directly or indirectly. Around 3,50,000 hectares of land in India are utilized for tomato farming, yielding 5.3 million tonnes of tomatoes and ranking India as the world's third-largest tomato producer. India is the world's second-largest producer of potatoes, with 48.60 million tonnes produced annually [21, 22]. India is the world's sixth-largest apple grower, with a production of roughly 2371.0 million tonnes. With a yield of approximately 116.42 million metric tonnes, India ranks second in rice production. Diseases squander more than 15% of India's crops, which ultimately weakens its economy. Agriculture today accounts for more than 10% of greenhouse gas emissions and 44% of water use in Europe, owing to the steady expansion of food production requirements [22]. Chemical treatments (pesticides) are widely employed to increase fruit crop market penetration, resulting in significant impacts on pollinators and the planet's environment. Plants account for more than 80% of the human diet. As a result, there is a growing interest in new approaches for reducing water consumption and optimizing pesticide treatments in order to protect natural resources. Thus, agriculture is in constant need of developing innovative ways to increase crop yields, as weather fluctuations, population growth, and food security make it difficult to expand. Agriculture is increasingly is being seen as a technology industry leader in terms of the advancement of artificial intelligence. Therefore, since this process is difficult or impossible for humans, we must automate with methods and tools to facilitate this with the decision-making.

Advances in computer vision, machine learning, and deep learning technologies can be utilized to identify crop diseases accurately, promptly, and earlier from a variety of existing crop diseases to meet the aforementioned issues in today's farming settings. Fast and exact results from computerized apprehensions employing image processing methods are among the benefits of implementing this technology. Computer vision and precision developments can be used to eliminate high labour costs and time waste, as well as improve crop quality and total production. Early information on the condition of the crop and the area of illness can aid in the spread of disease management through the use of appropriate delivery methods.

1.3 Research Contribution

Our research's significant contributions can be stated as follows:

1. The essential techniques in agricultural pre-harvesting automation chores such as soil and seed, crop disease detection, irrigation, weed control, pesticides, yield management, and so on are covered in this work.
2. We have discussed how ML in general and DL, in particular, have helped identify fruit and leaf diseases in plants. The role of IoT and smart agriculture, drones, and improved crop yield tasks, which consist of both image-processing approaches and other techniques involved in this process, are also discussed.
3. Various diseases and infections seen in various crops such as apples, grapes, bananas, and other fruits and vegetables, as well as their symptoms for classification purposes, are discussed. The steps involved in the automatic detection and classification of illnesses in plants are discussed, as well as the numerous strategies and algorithms that can be used in each phase.
4. Future promises and discussions, as outlined in this comprehensive study, are also offered, as are challenges and issues in the adoption of these machine learning models for smart agricultural chores.

1.4 Outline of the Paper

The rest of the paper is divided into four sections. The automation of the pre-harvesting tasks like soil and seed, disease diagnostics tools, crop phenotyping, irrigation control, pesticides management, crop yield, etc., occupy the core part in Sect. 2. Various types of probable diseases present in various plants such as tomato, rice, apple, and others are described, as well as the symptoms that may be utilized to diagnose and classify them. The generic steps involved in sutomatic plant disease detection and classification using machine learning and deep learning, such as image acquisition, data pre-processing, image segmentation, image extraction, and disease classification, are discussed in detail, as well as the various algorithms and techniques commonly used in each step.

The findings and the research potentials in smart agriculture and smart farming are discussed, debated, and presented in Sect. 3 as Discussions. Section 4 presents various challenges and open issues in the deployment of these machine learning and computer vision models for plant disease detection and classification, as well as future research directions, based on observations of various existing frameworks in the literature, are discussed in the paper. The size of the dataset and the classifiers employed have a significant impact on how these frameworks are displayed. As a result, Sect. 5 contains an attempt to summarise the existing research and issues identified in this study, as well as the paper's final remarks.. The complete layout of this manuscript is shown graphically in Fig. 5.

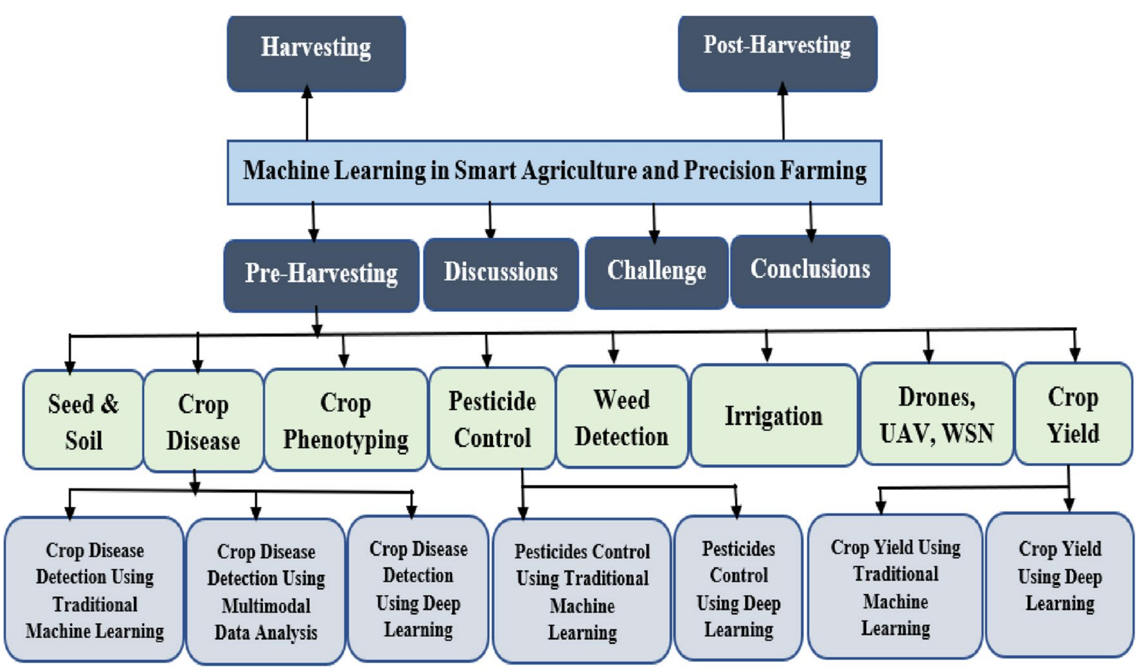

Fig. 5 Complete layout of the paper

2 Machine Learning in Smart Agriculture (SA) and Precision Farming (PF)

Eventually, farmers will need to use fewer resources to produce the same amount of food, reducing the amount of water used and decreasing the use of chemicals. With higher production and lower costs, farmers want to maximize the quantity and profitability while the public desires nutritious food. New products, practices, as well as new technologies are sought after in the agriculture industry. To meet these different needs, farmers can use precision agriculture. To remain innovative, agriculture must employ a combination of technologies that permits data collection and analysis. Many of these new technologies, especially web technologies, generate huge amounts of data for everyone to obtain and share. With regards to smart agriculture, the critical attributes of data mining are these: (i) It is imperative that we must deal with large amounts of data so we can explore that fast and effectively. (ii) For use in smart agriculture, the data sources need to be diverse; for example, sensors will need to be in various formats, as will images, strings, numbers, and so on. We must understand and communicate with various device types, along with websites, as well as pull information from the web.

The term ‘smart agriculture’ is used chiefly for soil and water use planning, monitoring crop health, and reducing pollutants, such as pesticides and herbicides [23]. Everything is becoming more brilliant in this fast-changing world of technology and agriculture. Performance relies both on historical data and on incorporating computer vision technology to meet the growing agricultural demand. While it does affect crop classification, agro chem production, disease detection, and prevention, it does not guarantee it.

All it takes is the place, the time, and the right product. Precision farming does away with repetitive and time-consuming operations, controlled agriculture, and labor-intensive part of farming with more accurate and controlled techniques than conventional ones [23]. When it comes to the use of communication technology in production systems, it’s viewed as an extension of existing equipment and the installation of sensors to be put into agricultural systems and state-of-the-art information processing like variable-rate technology, aerial and satellite-based sensors, as well as geographic information systems (GPS), all contribute to the current concepts of precision agriculture [24]. Livestock applications as well as the possible uses of satellite GPS are included under the umbrella of precision agriculture [24]. It also manages, integrates, measures, and analyses several technologies to enhance output while lowering the overall cost of the total process [25]. Profitability and productivity in agriculture would be significantly improved if soil conditions, available land, and equipment remained stable [26]. Image processing and computer vision have grown in recent years due to reduced equipment costs, increased computational power, and the corresponding reduced desire to use destructive methods has [27].

In the survey, technology such as GPS/GNSS, autonomous vehicles, the internet of things (IoT), and agricultural robots was found to be invaluable for precision farming. These four phases of precision farming include the process of gathering data, analyzing that data, making decisions, utilizing that data, and agriculture based on that data. In the last two decades, technologies have been developed using artificial intelligence to regulate temperature and humidity in artificially controlled greenhouses, i.e., ANNs and fuzzy controllers, for more precise farming practices have emerged. These autonomous mobile robots are used in farming for a diverse array of applications. Agriculture is a dynamic process in which constantly evolving robots have the ability to acquire new strategies to carry out their assigned tasks. The main characteristic of an autonomous robot has sensors that collect information and then convey it to the control unit. Fuzzy logic may be used to govern the robot control system.

While performing agriculture tasks, the steps as below is generally followed by farmers.

Step 1 Selection of Crop.

Step 2 Land Preparation.

Step 3 Seed Sowing.

Step 4 Irrigation & fertilizing.

Step 5 Crop Maintenance [use of pesticides, crop pruning, etc.]

Step 6 Harvesting.

Step 7 Post-Harvesting activities.

As per the above algorithm, the agriculture-related tasks are categorized in three major sub-areas. Figure 6 shows these three sub-domains of agriculture tasks. In the following sections, the review of the most recent techniques of machine vision systems used for classification and object detection in the pre-harvesting stage of farming is presented.

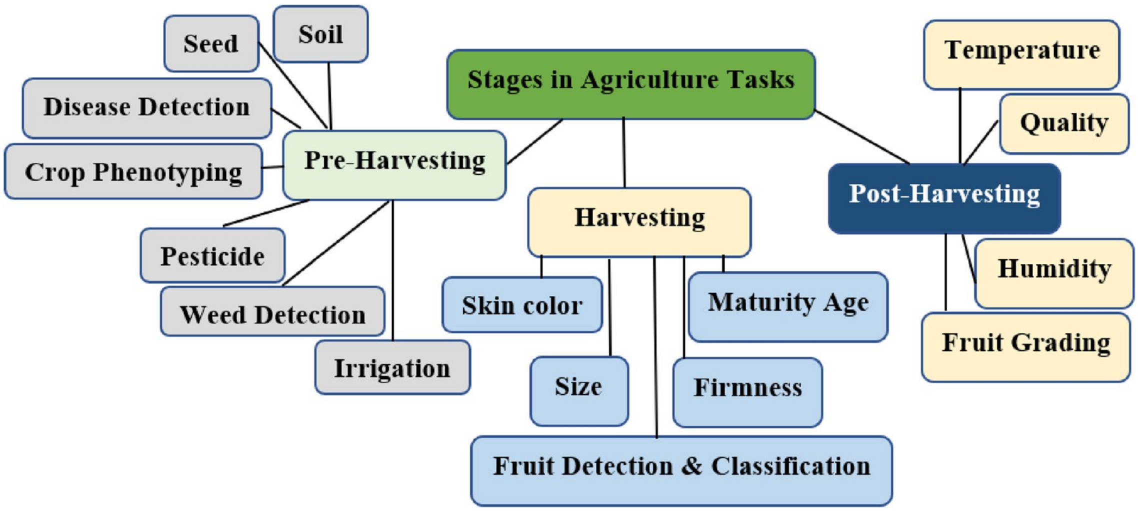

Fig. 6 General categorization and important parameters considered at each agriculture task

2.1 Pre-harvesting

The real growth of the crops is influenced by pre-harvesting conditions. Machine learning is utilized in pre-harvesting to record soil, seed quality, fertilizer treatment, pruning, genetic and environmental variables, and irrigation factors. It is critical to concentrate on each component in order to reduce total production losses. A few key pre-harvesting components are discussed, as well as how neural networks and machine learning are utilised to capture the parameters of each component in this section.

2.1.1 Seed and Soil

The classification and assessment of soil attribute aid farmers in reducing fertilizer costs, reducing the need for soil analysis experts, increasing profitability, and improving soil health. pH values and soil fertility indices classification and prediction model were presented by Suchithra and Pai [28]. pH values and Soil Organic Matter (SOM) are critical markers of soil fertility; according to Yang et al. [29], hence the authors predicted SOM and pH parameters in paddy soil. Organic carbon (OC), nitrogen (TN), and moisture content (MC) parameters of the soil have been predicted by Morellos et al. [30]. The goal of this research was to compare machine learning algorithms and linear multivariate algorithms in terms of prediction performance. Seed germination is a critical element in seed quality, which is a key determinant of yield and production quality. Huang et al. [31] and Zhu et al. [32] have shown applications of many computer vision, machine learning, and convolution neural network (CNN) algorithms in automated seed sorting amd soil quality estimations. Veeramani et al. [33] employed a CNN-based deep neural network (DNN) model to estimate the number of seeds per pod in soybeans and to categorize haploid seeds based on form, phenotypic expression, and embryo position. To improve the accuracy of the classification method, Keling et al. [34] employed a multilayer perceptron neural network model to separate high-quality pepper seeds from low-quality pepper seeds. A detailed summary of work done by different authors on soil and seed parameters is mentioned in Table 1.

2.1.2 Crop Disease Detection, Prediction, and Monitoring

Plants are vulnerable to infection because they are surrounded by the outside environment. The spread of disease depends on the current crop conditions and susceptibility to infection. It is crucial to identify plant diseases in order to avoid any losses in the yield and quantity of agricultural products. Ranging from leaves, stems, seeds, and roots of the plant to flowers, fruit, and seeds in the plant [35]. For many regions of the world, therefore, early diagnosis is problematic [36]. Smartphone diagnosis is increasingly being enabled by deep learning advances in computer vision. Risk reduction is critical because of the tedious task of spotting and then counting disease among large populations of crops on large farms; thus, automation is helpful. Even in underdeveloped countries, most infections are too subtle for the naked eye to be able to perceive, and for that reason, medical assistance is critical. Therefore, using image processing software to help classify diseases of plants became a high priority, given that many species could not be distinguished by looking at photographs alone.

The wide range of soil conditions and nitrogen levels are vital players in the good or bad health of crops. Pesticides were traditionally applied equally to each square of the field. If farmers are overly budgeting for the water

Table 1 Analysis of pre-harvesting parameters of soil and seed

References	Property	Dataset used (Public/own	Models/method/algorithms compared	Best model/method/algorithm	Results
Suchithra and Pai [28]	Soil	Public (reports available during the years 2014 to 2017)	Extreme Learning Machine (ELM) with different activation functions like sine-squared, Gaussian radial basis, triangular basis, hyperbolic tangent, and hard limit	ELMs with Gaussian radial basis function	80.00% of accuracy
Yang et al. [29]	Soil	Own	Four Machine Learning models Cubist regression model (Cubist), extreme learning machines (ELM), least squares-support vector machines (LS-SVM), and partial least squares regression (PLSR)	ELM	R2 = 0.81
Morellos et al. [30]	Soil	Own	Cubist, partial least squares regression (PLSR), least squares support vector machines (LS-SVM), and principal component regression (PCR)	LS-SVM is best for MC and OC, and TN is best by the Cubist	MC—RMSEP:0.457%, RPD:2.24 TN—RMSEP: 0.071 and RPD:1.96
Huang et al. [31]	Seed	Own	Ensemble learning, K-nearest neighbor (KNN), logistic regression, support vector machine (SVM), and Speeded Up Robust Features (SURF) algorithm to classify the extracted features, GoogLeNet, VGG19	GoogleNet	95.00%
Zhu et al. [32]	Cotton Seed	Own, dataset collected from Shihezi, Xinjiang Uyghur Autonomous Region, China	SVM, PLS-DA, and LR models based on deep features extracted by self-design CNN and ResNet models	self-design CNN 80%	80.00%
Veeramani et al. [33]	Haploid maize seeds	DeepSort, Support Vector Machine (SVM), Random Forest (RF), and Logistic Regression (LR)	DeepSort	DeepSort	fivefold cross-validation
Keling et al. [34]	Pepper seeds	Own	Multilayer perceptron (MLP); BLR binary logistic regression, single feature models	multilayer perceptron and binary logistic regression	90.00%

use on their farms, it significantly reduces the number of species that are pollinators for flora and fauna. ML can be used in conjunction with analysis software for crop health assessment. The data is used to pinpoint which infestation areas are most critical, thus allowing farmers to target pesticide usage in those specific locations. Environmental customization can be significant. An example of this is Plantix, a German start-up, which combines machine learning with image recognition in an app to identify plant diseases and nutrients. Tools like these really make a difference for smaller farmers because they're flexible. Bigger businesses use digital platforms connected to the internet of things (IoT) devices to collect both visual and thermal data. A concept commonly used by Swiss-based companies, for example, such as Gamaya, employs precisely this practice. Trace Genomics' approach to soil health differs in that it looks at soil quality and how the particular plant species respond to the quality of the soil rather than at the conditions that surround them. ML is used to keep crops healthy so that the company is trying to prevent disease instead of finding it. Some farmers ship their soil directly to Trace Genetics and receive an evidence-based answer about the soil condition in advance. Here, a detailed survey of the recent techniques in computer science for automated disease diagnosis and detection in the agricultural domain is performed.

2.1.2.1 Detecting and Classifying Crop Diseases Using Conventional Data Mining Methods Computer vision can use various classification and detection algorithms and methods for crop disease. Using deep convolution neural networks (DNNs) helped [37] to achieve a 99.53% correct result in diagnosing the plant disease. Neural networks have also been applied to issues in rice, like identifying illness [38]. Generally, principal component analysis (PCA) [39], support vector machines (SVM) [40], and multiple linear models [41] are alternative models most often used in the smart farming context. In an experiment, it was found that K-means clustering [42] for the classification of healthy and infected leaves was more effective and that support vector machines (SVM) provided a better solution than an artificial neural network (ANN). While discovering and classifying their visual similarities, Bashir and Sharma [43] found color and texture to be helpful in agriculture and horticulture disease detection techniques. The start-up Prosper developed a system that consists of networked cameras, sensors, and an algorithm based on machine learning to keep track of crops and notify farmers as soon as they're sick [44]. By applying neutral network processing procedures to hyperspectral data, Golhani et al. [45] concentrated on the study of plant disease. Mosh et al. [46] used multilayered neural networks to find yellow rust in wheat. Using ANN technology, class performance rose from 95 to 99%.

Based on an experiment conducted by Rangan et al. [47], where they generated a dataset of six types of tomato leaves from PlantVillage for the classification of tomato crop disease. Both the AlexNet and the VGG16 net used a deep learning architecture, and the dataset from PlantVillage was used as input to it. The accuracy of classification of VGG16's 13,262 image signatures was 97.29%, and of AlexNet's was noted at 97.49%. Machine vision techniques are more effective in identifying plant disease at the beginning stages of growth rather than the late stages [48]. The start of the process begins with the preparation and acquisition of a sample. The machine vision process has been applied to crops like rice [49], papaya [50], and chili pepper [51] with accuracies of 87.9%, 87.5%, and 90.15%, respectively. Figure 7 displays a demo of the diseases in banana and rose leaves.

The SVM classifier was used by researches to detect grape leaf disease in [52]. Powdery mildew & DownyMildew are two grape plant diseases that were identified with an accuracy rate of 88.89% in [53]. In [54], authors detected diseases, such as anthracnose and canker on oranges, limes, lemons, and grapefruit citrus trees. The research outcome received a true accuracy rate of 95%. The authors showed an overall classification accuracy of around 90% [55] while detecting septoria leaf blight, frog eye, downy mildew, diseases in soybean crops by using a large dataset. The authors of [56] designed a system for diagnosing diseases in tea crops and detecting 3 different diseases by using limited features and claim to have gained 90% accuracy rate. In [57], authors developed a system to determine disease presence in wheat crop photos with a fuzzy classifier. The accuracy of unhealthy and healthy leaves classification was 56% and 88%, respectively. A thorough survey on crop diseases identification with the KNN classifier is performed in [58]. The authors [59] used the GLCM feature extraction approach with the KNN classifier for cotton crop disease (Grey Mildew) and achieved 82.5% accuracy. An in-depth data of plant diseases detection using an ANN classifier is offered in [60]. The authors [61] analyzed various supervised machine learning algorithms like RF, SVM, DT, KNN, NB, and KNN with image processing methods to uncover the best algorithm for plant disease classification. RF algorithm achieved 89% accuracy compared with other algorithms.

Similarly, the authors [62] evaluated the performance of SVM, RF, Stochastic Gradient Descent (SGD)) & DL (Inception-v3, VGG-16, VGG-19) in terms of citrus plant disease detection in which DL methods overtook the ML methods. The work [63] illuminates various types of plant disease (PD), different progressed ML & image processing techniques to identify plant PD. [64] aimed at tweaking & assessing cutting-edge deep CNN for picture-based PD characterization. Hossain et al. [65] proposed a method for plant leaf disease detection (PLDD) & characterization utilizing

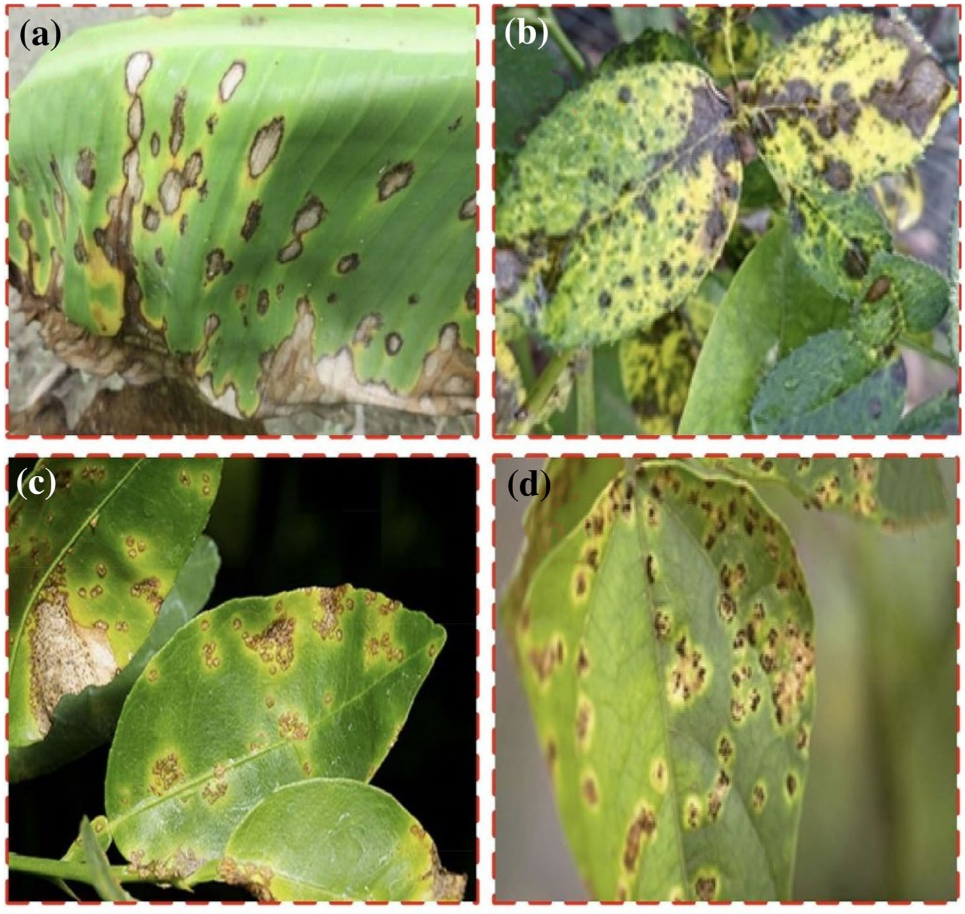

Fig. 7 Diseases in plants (**a**, **b**) Banana leaf disease, (**c**, **d**) Rose leaf disease

the KNN classifier. An improved artificial plant optimization (IAPO) calculation using ML has been presented in [66] that distinguishes the PD & arranges the leaves into sound & tainted on a dataset of 236 pictures. Arora and Agarwal [67] gave the acknowledgment and categorization of maize plant leaf illnesses by utilizing a deep forest method. In [68], a global pooling dilated CNN (GPDCNN) is suggested for recognizing PD. The authors in [69] developed a vision-based program to detect symptoms of olive quick decline syndrome (OQDS) on leaves of Olea europaea. Again, a convolutional neural network for end-to-end detection of red grape vine (Sangiovese) using color images of leaf clippings is recommended by [70].

In [71], researchers developed a system to detect disease in glycine max with a k-means based segmentation algorithm. The design catches downy mildew, frog eye, and septoria leaf blight from images collected by the PlantVillage project. Again, in [72], the authors proposed an intensity thresholding method for measuring the progression of powdery mildew in cherries. A hybrid method detecting and identifying diseases in citrus plants is presented in [73]. An approach based on color difference to segment diseased parts of known mandarin leaves is given [74]. A method to detect diseases in beans using CNN is offered in [75]. The research is carried on wheat disease detection in [76] and banana field images in [77]. The study in [78] proposed a method to classify apples into rotten or good apples and found SVM as the best classifier with 98.9% performance. An approach for apple leaf disease detection that achieved 98.54% classification accuracy is given in [79]. The work in [80] investigated the use of KNN and SVM for detecting of leaf deficiencies and leaf diseases. A hybrid method for detection and classification of diseases in citrus plants is recommended in [81] and achieves 97% classification accuracy on the citrus disease image gallery dataset. Table 2 gives an idea of the state of the art works on automated disease detection in the agriculture domain. Figure 8 displays the sample of different stages of grape leaf disease.

2.1.2.2 Detecting and Classifying Crop Diseases Using Multimodal Crop Data Analysis Hybridizing data from both hyperspectral and multi-spectral imaging allowed for early detection of disease performed by the authors in [93] and attained 94.5% accuracy. The authors here propose a Hydra, which provides for multivalued data fusion, application event identification, and makes better decisions based

Table 2 A summary of the papers dealing with detecting and classifying diseases using conventional data mining methods

References	Treated diseases	Methods	Precision (%)
Padol and Yadav [82]	Grape leaf diseases: Powdery mildew, downy mildew	Image processing by SVM	88.99
Warne and Ganorkar [83]	Cotton leaves diseases: Red leaf spot, cercospora leaf spot, alternaria leaf spot	Image processing by NN	89.56
Kaur and Singla [84]	Potato late blight (leaf disease)	Image processing by ANN	100.00
Patil and Zambre [85]	Cotton leaf spot disease	Image processing by SVM	89.00
Revathi and Hemalatha [86]	Cotton leaf spot diseases	Image processing by NN	98.10
Sannakki et al. [87]	Grape leaf diseases: Powdery mildew, downy mildew	Image processing by BPNN	100.00
Dubey and Jalal [88]	Apple rot, Apple scab, Apple blotch	Image processing by SVM	93.00
Barbedo [89]	Plant disease	GoogLeNet CNN	96.17
Liu et al. [90]	Apple leaf disease	AlexNet precursor, VGG 19, inception, DenseNet, ResNet, PlantDiseaseNet, SVM BP AlexNet GoogLeNet ResNet-20 VggNet-16	97.62
Kour and Arora [91]	Apple Fruit disease	Fuzzy rule-based approach for disease detection (FRADD)	91.66
Turkoglu and Hanbay [92]	Plant disease and pest detection	Extreme learning machine (ELM), support vector machine (SVM), and K-nearest neighbour (KNN), VGG16, VGG19, and AlexNet	98.00

Fig. 8 **a** Healthy control, **b** Grapevine yellow (GY) caused by Flavescene doree (FD), **c** Grapevine Leafroll and **d** Stictocephala Biosonia

on the data [94]. The elements can be grouped using different techniques: Low-level, medium-level, and high-level. Again, the grouping can be performed using different levels (decision fusion based on multiple applications). Two apps were developed with Embrapa (Brazilian Agricultural Research Corporation) in partnership with the smart agriculture domain: One provided data and information on best practices to help farmers; the other, information on how to apply them in small-scale water harvesting. The first step was to find out if there was a critical moisture level, and the second step estimated adequate irrigation time was done by measuring crop evaporation (transpiration from the soil) [94]. Figure 9 displays the sample of all apple disease leaves on different stages.

2.1.2.3 Detecting and Classifying Crop Diseases Using Deep Learning This section provides a brief summary of different DL methods for the transformation of traditional agriculture into a creative and intelligent practice. A plant disease detection model was constructed using the Berkley vision and learning center DL framework [95]. The model is able to identify 13 different types of disease. An approach proposed in 2017 that combined CNN and K-means feature for plant disease identification and suppression is put forward in [96]. Identifying and generalizing features may lead to the degradation of consistent results due to human errors in creative design. This indicates that the application of DL and K-means resulted in a 92.89% accuracy of recognition [97].

Istanbul Technical University says in 2017 that CNN algorithms outperform feature-based learning algorithms in discrimination of phenological stages [98]. A new deep learning model for plant phenotype was proposed by Namin et al. [99]. New LSTM designs were created by combining CNNs. While CNN is particularly beneficial for reducing the

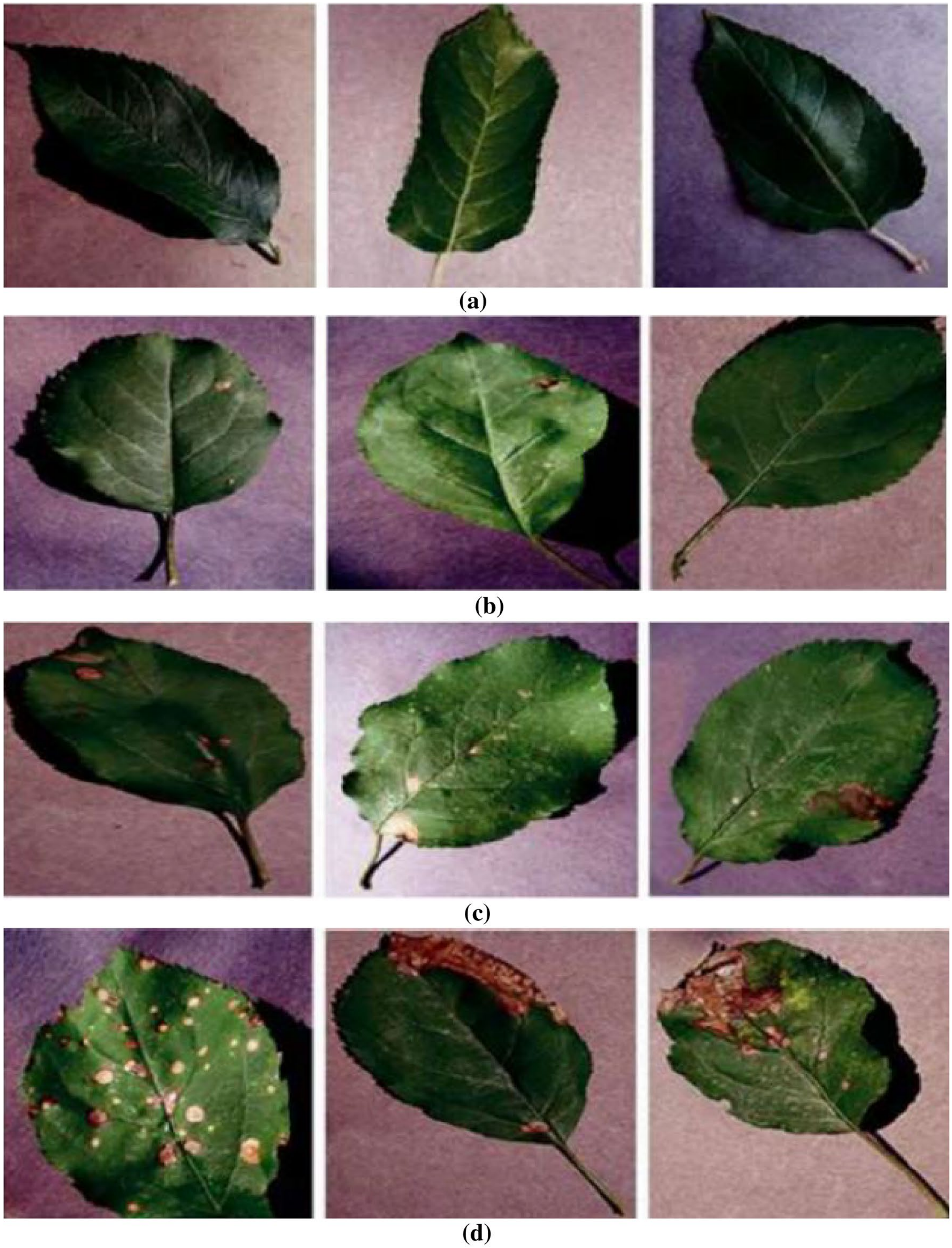

Fig. 9 Sample of Apple Leaf Images at all stages **a** Healthy Stage, **b** Early Healthy Stage, **c** Middle Healthy Stage, **d** End Healthy Stage

error from sensor readings due to its time-series data [100], RNN is additionally used for crop yield prediction, which uses a time series approach to reduce sensor-derived bias. The work in [101] implements two RNN-based classifiers, one a long short term memory unit (LSTM) model and another a gated recurrent unit (GRU), in winter plant phenology mapping to find out how much water to give the crops and the crop environment. Table 3 presents state-of-the-art

Table 3 A summary of the papers dealing with the task of detecting and classifying diseases using deep learning

References	Title deep learning	Algorithms used
Yu et al. [102]	Dual-camera high throughput phenotyping (HTP) platform on an unmanned aerial vehicle (UAV) for large scale soybean yield	CNN-RNN
Chu and Yu [103]	An end-to-end model for rice yield prediction using deep learning fusion	Propagation Neural Networks (BPNNs) and Independently Recurrent Neural Network (IndRNN)
Tedesco-Oliveira et al. [104]	Convolutional neural networks in predicting cotton yield from images of commercial fields	Convolutional Neural Networks (CNN)
Nevavuori et al. [105]	Crop yield prediction with deep convolutional neural networks	Convolutional Neural Networks (CNN)
Maimaitijiang et al. [106]	Soybean yield prediction from UAV using multimodal data fusion and deep learning	Deep Neural Networks (DNN)
Yang et al. [107]	Deep convolutional neural networks for rice grain yield estimation at the ripening stage using UAV-based remotely sensed images	Convolutional Neural Networks (CNN)
Khaki and Wang [108]	Crop Yield Prediction Using Deep Neural Networks Deep Neural Networks (DNN)	Convolutional Neural Networks (CNN)
Rahnemoonfar and Sheppard [109]	Real-time yield estimation based on deep learning	Convolutional Neural Networks (CNN)
Chen et al. [110]	Strawberry Yield Prediction Based on a Deep Neural Network Using High-Resolution Aerial Orthoimages	Faster Region-based Convolutional Neural Networks (Faster R-CNN)
Sun et al. [111]	County-Level Soybean Yield Prediction Using Deep CNN-LSTM Model	The combination of Convolutional Neural Networks and Long-Short Term Memory Networks (CNN-LSTM)
Khaki et al. [112]	A CNN-RNN Framework for Crop Yield	Prediction The combination of Convolutional Neural Networks and Recurrent Neural Networks (CNN-RNN)
Terliksiz and Altylar [113]	Use Of Deep Neural Networks For Crop Yield Prediction: A Case Study Of Soybean Yield in Lauderdale County, Alabama, USA	3D Convolutional Neural Networks (3D CNN)
Lee et al. [114]	A Self-Predictable Crop Yield Platform (SCYP)	Based On Crop Diseases Using Deep Learning Convolutional Neural Networks (CNN)
Elavarasan and Vincent [115]	Crop Yield Prediction Using Deep Reinforcement Learning Model for Sustainable Agrarian applications	Deep Recurrent Q-Network
Wang et al. [116]	Winter Wheat Yield Prediction at County Level and Uncertainty Analysis in Main Wheat-Producing Regions of China with Deep Learning Approaches	The combination of Convolutional Neural Networks and Long-Short Term Memory (CNN-LSTM)
Ju et al. [117]	Machine learning approaches for crop yield prediction with MODIS and weather data Long-	Short Term Memory (LSTM) Convolutional Neural Networks (CNN), Stacked-Sparse Autoencoder (SSAE)

deep learning works on automated disease detection in the agriculture domain.

The authors in [118] used deep learning (DL) to detect powdery mildew (PM), persistent fungal disease in strawberries to reduce the amount of unnecessary fungicide use, and the need for field scouts. ResNet-50 gave the highest CA of 98.11% in classifying the healthy and infected leaves; however, considering the computation time, AlexNet had the fastest processing time, at 40.73 s, to process 2320 images with a CA of 95.59%. The four selected CNNs, AlexNet, SqueezeNet, GoogLeNet, and ResNet-50 were found to be commonly used in agriculture applications [119]. In [120], authors evaluated AlexNet and SqueezeNet for detecting disease in tomatoes and yielded similar accuracies. Similarly, GoogLeNet (Inception), has been used for disease detection in cassava [121, 122]. Lastly, [123] compared different versions of the ResNet algorithm for detecting tomato diseases, where it was determined that ResNet-50 outperformed ResNeXt-50. The authors [124] trained a deep convolutional neural network to identify 14 crop species and 26 diseases. The trained model achieves an accuracy of 99.35% on a held-out test set, demonstrating the feasibility of this approach.

2.1.3 Crop Phenotyping

The total of all observable characteristics of an organism can be defined as phenotype. The essential features may include personality, biochemical properties, size, and color. The plant's ontogenic, physiological, anatomic, and biochemical characteristics vary with the stage of development, while it has constant morphological characteristics [125]. Additionally, during growth and development, the phenotype incorporates an enormous number of functions, structures, processes, and structures [126]. For cultivar development, successful breeding, efficient phenotype evaluation are required. Research bears that the main challenge in plant breeding is improving the yield.

In order to increase the time and lower the cost of data acquisition and analyses, Dee and French [127] aimed to propose an automated system that could identify and measure objects from an image without human assistance in 2015. Coppens et al. in 2017 [128] presents advances in robotized imagery characterization techniques which allow increases in the number of phenotype evaluations, mitigating the supposed measurement bottleneck for functional genotyping research. In 2016, Bai et al. [129] utilized five different types of sensors, ultrasonic distance sensors, portable spectrometers that use red, green, RGB cameras, and near-infrared spectroscopy for high throughput phenotyping in plant breeding and developmental phenotyping. There are four different hyperspectral sensor technologies: push broom, filter-based, non-imaging, and two, which are specialized for various purposes. They may be used for the resistance of a particular disease in agriculture, however.

Another prominent example of a set of an application of mathematical algorithms to classification is the simplex volume maximization (SVM) approach [130]. SVM methods are primarily applied in the literature for classification and stress phenotyping [131]. However, an improved understanding of the process may make it possible to apply methods such as K-means clustering, ANN, Gaussian Mixture Models, etc., more efficiently. Autonomous ground vehicles can be used for things like a telepresence robot that can test plant stalks for strength and gather plant genetic data with an array of sensors that does not make contact, more importantly [132]. Another phenotypic platform is a metaphorical platform [133]. Autonomous ground vehicles (Vinobot) and mobile observation platforms (Vinoculer) work together to form an architecture [134]. This is advantageous because the ground vehicle could be outfitted with sensors to obtain specific information about individual plants, while the lookout tower could monitor an entire field and focus on particular specimens. Remote sensing and on-the-the-the-ground technologies are yet another way to access or collect data [135]. Deep Phenomics (pre-trained neural networks) provide pre-trained models for phenotyping, as well as personal application to plant scientists [136]. Three experiments were performed to evaluate the image-based phenotype tasks: the leaf counting test, the classification of mutants, and the age-regression work. Reynolds et al. [137] studied cost-effective imaging devices and environmental sensors, focusing on their trade-off in investment. Lowering the cost of ecological sensors [138] or embedded mobile phone sensors [139] has allowed new options such as "affordable phenotyping" or "cost-effective phenotyping" to emerge in recent years. The crop phenotyping process is depicted in Fig. 10 below.

2.1.4 Optimised Management of Input Fertilisers and Pesticides

Filtration of soil involves enormous effort and money. That study found that a conservative estimate says about 5.6 billion pounds of pesticides are applied every year globally. Pattern recognition and decades of crop conditions allow an effective reduction in pesticide usage. Identifying pests is made easier with image-based pest control apps, and then one can use an app to guide in finding the proper one. Agents help deliver only the appropriate amount of pesticides to the crop, as excessive quantities can be dangerous to humans. Diverse environmental conditions, such as improper temperature and humidity during plant production cycles, allow plant pathogens, such as fungal and nematode microorganisms and rodents to proliferate. Thirty years ago, products for farmers that contained agrochemicals started appearing on the market and rapidly changed agriculture. With new

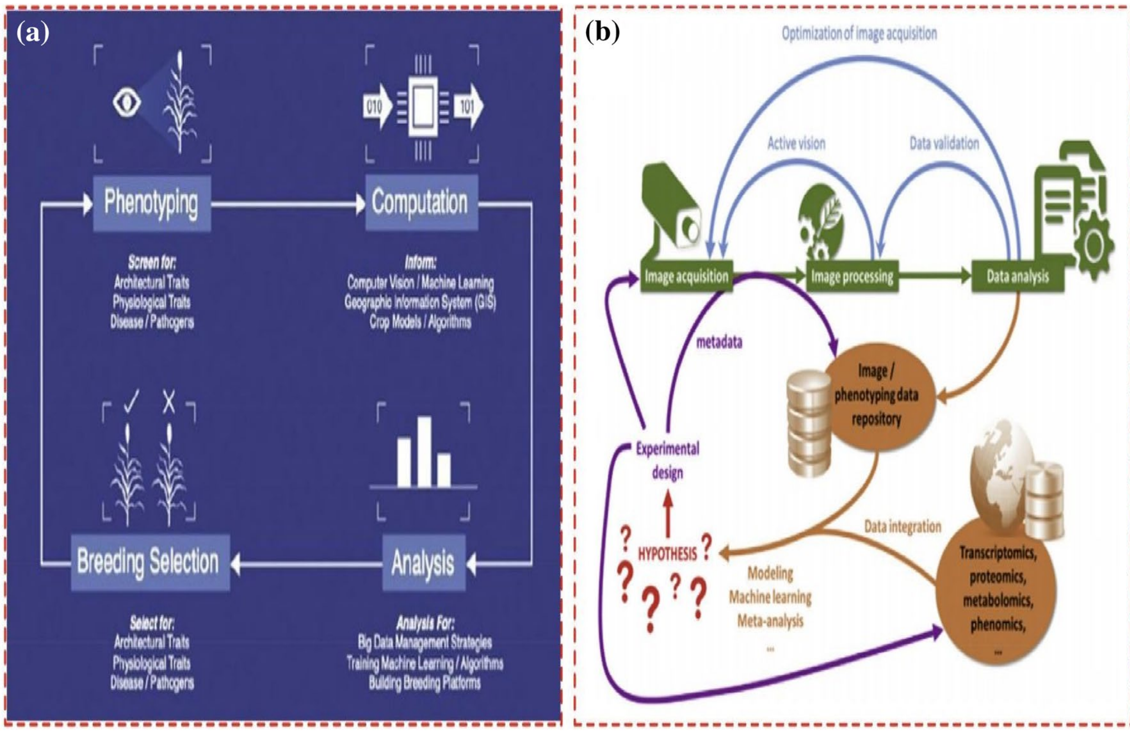

Fig. 10 Crop phenotyping process. **a** Computation for Phenotyping diagram [140], **b** Image acquisition for Phenotyping [141]

technological advances in chemical treatments, including pesticides, antibiotics, and insecticides, farmers finally made unwanted insects and bacteria less of a problem. Of course, crop damage is lessened by using these chemicals, but on both the environment and human health, and it does so in different ways like more environmentally friendly and less toxic chemicals. The researchers at the University of Delhi were able to produce chemicals only for specific insect species using ML tool-based technology called NeuroPIpred. However, in insects and certain other animals such as mollusks, so-like neuropeptides are considered necessary for all of their biological and behavioral activities such as metabolism and reproduction. NeuroPIpred takes in an insect neuropeptide composition and turns this into a new kind of insect poison that kills only the target species. Agrochemical pollution has been a worldwide concern for the past few decades.

2.1.4.1 Pest Detection Using Conventional Data Mining Methods Several works have been carried out by the researchers for rice pest detection. Zhou et al. [142] proposed an enhanced area-based fully convolutional networks panicle identification and counting system in order to detect and count the rice in the field, and this system can be used to automate the rice phenotype measurements. Liu et al. [143] proposed a UAV-based computer vision system to identify the agricultural airboat position information, which is used in autonomous fertilizing as well as herbicide applications. The presented system can inspect the paddy field with the help of UAV. Barrero et al. [144] proposed a method to fuse high resolution RGB and low-resolution multispectral images for identifying the Gramineae weed in case of rice fields dealing with plants by considering fifty days after emergence. Li et al. [145] focus on Capsnet to track rice images. The Capsnet is used to train classification, and the output vector is predicted by focusing on routing by agreement protocol. Kitpo et al. [146] proposed an IoT-based drone implementation system for the detection and classification of rice diseases. Qin et al. [147] focus on the impact of spraying parameters such as operation velocity and height of UAV on the droplet deposition in the case of rice canopy as well as the protection efficiency against the hoppers (plant). Table 4 gives the state of the art works on automated pesticide tasks in the agriculture domain.

2.1.4.2 Pest Detection Using Deep Learning Methods The authors in [156] present an embedded system enhanced with ML functionalities, ensuring continuous detection of pest infestation inside fruit orchards. The embedded solution is based on a low-power embedded sensing system along with a neural accelerator able to capture and process images inside common pheromone-based traps. Results show how it is possible to automate the task of pest infestation for unlimited time without the farmer's intervention. Deep learning techniques have been used to achieve an entirely automated,

Table 4 A summary of the papers dealing with the optimal use of fertilizers & pesticides in smart agriculture context

Reference	Goal	Technique	Used data
Boniecki et al. [148]	Prediction of 6 types of pests in an apple orchard	Neural Networks	Digital images of pests
Tripathy et al. [149]	Predicting pests/diseases	Gaussian Naive Bayes, Rapid Association Rule Mining and Multivariate Regression Mining	Temperature, soil temperature, relative humidity, leaf wetness, and other weather data
Rodrigues et al. [150]	Predicting pests/diseases	Interval Fuzzy Logic	Temperature data, humidity data
Rupnik et al. [151]	Prediction of Pests (population size and its dynamics)	Random Forest, Time series analysis:	Data of pest
Lottes et al. [152]	Detection of beet sugar plants/weeds	Random Forest, Random Markov Field	Images of two different fields captured by robots
Yu et al. [153]	Detection of weeds	DCNN	Images taken at different places
Bosilj et al. [154]	Detection and classification of crops and weeds	SVM	Vegetation images
Padalalu et al. [155]	Suggestion of the amount of fertilizer and irrigation control	Naive Bayes algorithm	Sensor data (temperature, moisture, and PH) and weather forecast data

real-time pest monitoring system by removing the human from the loop [157]. Lima et al. [158] is one of the recent works that exploit ML techniques to classify insects. The researchers [159] build a deep learning model having the ability to explore the meaningful features in the task of classification automatically that actually prepare a complete roadmap in order to detect the seriousness of the disease. The VGG model reached its best, having an accuracy of 93.5% over existing validation data. Barbedo [160] worked on image segmentation method to identify plant diseases in black and white background and try to reduce human error while taking less time in identifying these diseases. Many of the papers [161, 162] on image-based plant diseases identification follow some basic approaches for pre-processing by removing the background and segmenting the lesion tissue of the diseased plant. In [163], the authors have discussed the detection of the unhealthy region of plant leaves; they have used minimum distance criteria and an SVM classifier on the plant leaf diseases using texture features. In [164], the authors propose a method to detect infections in apple fruit and timely prevention of further infections caused by environmental factors and claimed to have achieved 88% recognition rate. Jiang et al. [165] proposed a CNN model for apple leaves disease detection by improving CNN for real-time detection of the disease from an image dataset. A new mobile application to automatically classify pests using a deep-learning solution for supporting specialists and farmers is introduced in [166]. The study has been successfully validated on five groups of pests; called Aphids, Cicadellidae, Flax Budworm, Flea Beetles, and Red Spider, and the method displayed 99.0% accuracy. Various capabilities of state-of-the-art (SoA) object detection models based on CNN for the task of detecting beetle-like pest insects on non-homogeneous images is studied in work [167]. The authors in [168] developed a disease detection tool for banana plants with five different CNN architectures. Table 5 gives some more state-of-the-art works on automated pesticide tasks in the agriculture domain.

Table 5 A summary of the papers of optimal use of fertilizers & pesticides in smart agriculture context using deep learning

Author	Dataset used	Best model	Testing accuracy (%)	Number of training parameters
Sanga et al. [168]	Banana leaf images obtained from banana field	ResNet-152	99.2	60 million
Chohan et al. [169]	PlantVillage	VGG-19	98.3	143 million
Ferentinos [170]	PlantVillage	VGGNet	99.5	138 million
Mohanty et al. [171]	PlantVillage	GoogLeNet	99.3	7 million
Mohameth et al. [172]	PlantVillage	ResNet-50 + SVM	98	25 million
Tiwari et al. [173]	Potato leaf extracted from PlantVillage dataset	VGG-19 + Logistic Regression	97.8	143 million
Khamparia et al. [174]	Tomato, potato, and maize leaf extracted from PlantVillage	CAE	86.78	3.3 million
Punam Bedi [175]	Bacterial Spot disease in peach plants	CAE + CNN	98.38	9914

2.1.5 Weed Detection and Management

Weeds proliferate, interfere with yield and profits, followed by fungus. Currently, they are the most popular choice, but in terms of both effectiveness and cost, herbicides are problematic. Secondly, the longer herbicides are left in the soil, the more weeds are developing resistance to them and can survive. The system is about to fundamentally change how farmers detect infested regions. Autonomous herbicide-spraying has been implemented by California-based Blue River Technology's creation, called See & Spray, which can select and dispense herbicides only on unwanted plants. The technology reduces the amount of chemicals required by 80%. Tailoring herbicide programs is also made easier because of the use of See & Spray's weed profiling feature. Extreme over-irrigation is a risk factor for pseudomonas, amoeba, and larvae of eels and parasites and biocides (pharmaceuticals, chemicals, etc.) in the produce. Many data-mining techniques have been developed to study the need for various crop and growth cycles for irrigation systems. Data mining is critical to measuring the consumption and distribution of water using climatic elements, crop factors, and economic factors. In a farm, it is imperative to have control of the pests. Many researchers have studied plant mapping by using ML, though [176, 177]. Lots of unmanned aerial mapping machines for doing optimization of the field have been designed and used. IoT-controlled flying machines NB-IoT is suitable for handling and shaping a large amount of data. Table 6 gives some more state-of-the-art works on automated weed detection in the agriculture domain.

2.1.6 Water Analysis and Optimal Irrigation

If the fields are to be productive, they must be irrigated frequently. ML uses historical data to ensure adequate irrigation of each field's unique moisture levels. Optimal irrigation had been a challenge for farmers in the past, but now machine learning has taken care of it. The ML robots can also measure the moisture of the field in real-time and ensure that irrigation water application on all points of the field is allocated in an isobotonic pattern. Even with traditional agriculture, it is impossible to accomplish this on the cheap. The necessity of the water to the global food supply can be imagined, given that 70% of global freshwater is for irrigation. Especially in regions where rainfall is scarce, water management is critical. Nevertheless, here again, this has more to do with the environment as the global population and food consumption are increasing. This is a problem in the worldwide market, and ML-powered smart irrigation solutions could help to solve it. Advanced meteorological and geographic sensor systems are connected to multiple in-field sensors or satellites that can measure the temperature,

Table 6 Machine learning techniques for weed detection

Author/year	Problem definition	Targeted crop	Dataset	Model	Accuracy (%)
Alam et al. [178]	Crop/weed detection and classification	Unspecified	Images were collected from private farm	RF	95
Tu et al. [179]	Measuring Canopy structure	Avocado tree	Avocado field Bundaberg, Australia	RF	96.00
Gao et al. [180]	Weeds recognition	Maize	Images were taken from crop field of Belgium	RF KNN	81.00 76.95
Castro et al. [181]	Early Weed mapping	Sunflower, cotton	Images were taken from crop field of Spain	RF	87.90
Aaron et al. [182]	Weed detection by UAV	Maize	Images were collected from private farm	NVDI digit, YOLOv3 Detector	98.00
Chabot et al. [183]	Monitoring water aquatic vegetation	Stratiotes aloides	Trent-Severn Waterway in Ontario, Canada	RF	92.19
Brinkhoff et al. [184]	Land cover mapping	9 perennial crops	Images were taken from the Riverina region in NSW, Australia	SVM	84.80
Zhang et al. [185]	Weeds species recognition	8 weed plants	1600 weed images were taken from South China crop field	SVM	92.35
Adel et al. [186]	Weed detection using shape feature	Sugar beet	Images were taken Shiraz University, Iran	SVM	95.00
Abouzahir et al. [187]	Weeds species detection	Soybean	Images were collected from Sâa José farm, Brazil	SVM	95.07
Maria et al. [188]	weed mapping using UAV-imagery	Sunflower, maize	Images were collected from a private farm	SVM	95.50
Faisal et al. [189]	Classification of crops and weed	Chilli	Images were Collected chilli field	SVM	97.00

moisture, rainfall, and growth data. Given enough data, the irrigation system becomes smart and minimizes efforts to use water while increasing water use. For example, among other things, California-based ConsertWater uses satellite data, weather, topography, and geographical location to determine the amount of water required for a particular field. The app's beauty is that it doesn't require ground sensors to be installed and works all the time. Even though the app looks simple, it claims to save 30% of the water that's used by farmers.

Several methods for water control in an agricultural setting, as well as a water quality analysis, have been implemented [190, 191]. An automated irrigation system to conduct the study of water needs in the field is proposed in [192]. These sensors are installed throughout the field to gather data regarding different factors, namely soil moisture, soil temperature, and soil composition (PH). The Naive Bayes technique is used to estimate the required amount of water. For an agricultural operation, this technique considers the weather forecasts to regulate the amount of water supply to be applied to the crops and recommends specific fertilizers. Perea et al. [193] propose an intelligent irrigation system that ensures a just and well-considered use of water by integrating the Decision Tree with the Non-Dominated Sorting Genetic Algorithm II (NSGA II) genetic algorithm.

Xie et al. [194], in 2017, suggest a smart irrigation system consisting of the components: A solar demand estimation used to determine the time and energy required to do the following task using the support vector regression method, and on-demand scheduling is used to reduce the cost of irrigation. This feature takes advantage of numerical weather prediction (NWP) and incorporates it into the time of use model (TOU). Results showed that water and energy resources could be saved by 7.97%, and this resulted in a total amortization of 25.34%. Kokonis et al. [195] made a case for using a fuzzy neural network for irrigation by suggesting the FITRA. The algorithm determines how much water the irrigation should be applied based on data. To cut down on water consumption, several sensors are used to increase production and maximize moisture levels. Goldstein et al. [196] devised an irrigation recommendation system in 2018. Several regression and classification algorithms were applied using a number of prediction models. Data from different sources, including weather sensors, meteorological, and sensor-based systems, was utilized to make real-time control possible. The authors [197] proposed a novel CNN calibration method for the NIR image data. Its architecture is extremely simple, with one layer of convolution and one layer of pooling layer. In a data-driven way, the decision tree algorithm was used to extract the most informative features.

The work [198] proposes a framework that enables advanced fuzzy logic to control a pump's switching time according to user-defined variables, whereby sensors are the central aspect of and contributor to the system. An overview of IoT-based irrigation systems for agriculture is presented in [199]. A review of monitoring and control mechanisms for precision irrigation systems is considered in [200]. IoT technologies, practices, and future studies are investigated in [201] for smart agriculture, and important agricultural applications are highlighted and discussed. In these studies, a detailed survey is carried out on smart agricultural monitoring in both simulated and real environments. A LoRaWAN and fog computing-based architecture for deploying smart irrigation systems is proposed in [202]. In [203], a graphical user interface application for multifractal analysis of soil and plant structures is presented for Windows platforms. In [204], a user-friendly mobile application called REUTIVAR-App for fertigation scheduling using reclaimed water is presented in olive groves, and daily real-time irrigation and fertilization schedule recommendations at farm scale are monitored. In [205], the authors developed an algorithm named optimized algorithm of sensor node deployment for agricultural (OASNDFA) for intelligent agricultural monitoring based on an optimized theory for the least required sensor nodes in agricultural fields. The authors in [206] used drone remote sensing techniques to detect trees with similar symptoms to trees infected with PWD. The SVM had an overall accuracy of 94.13%, which is 6.7% higher than the overall accuracy of the ANN, which was 87.43%. The study proposes developing the low-cost unmanned aerial system (UAS) for precision agriculture tasks called AgriQ [207]. Table 7 gives some more state-of-the-art works on automated irrigation control in the agriculture domain.

2.1.7 Harvesting Robots, Drones, Unmanned Aerial Vehicles (UAV), and Wireless Sensor Networks (WSN) in Smart Agriculture

For large-scale farming, labor costs form a significant part of farming expenses. Like many other steps in traditional plantation agriculture, harvesting, too, uses an enormous workforce. Anything that causes the crop to remain unharvested will lower the return on investment. Robotic harvesters identify and extract the crops at the appropriate stage. This is both good for saving on labor costs and helps assure that the quality of the harvest is preserved and delivered to the customer at the right time and in the process. The ML techniques and tools employed in crop production also show up in livestock production. The machines do the work and supervise or manage the farms. The datasets are combined to aid in the diagnosis of disease and/damage detection. This example, as shown here in Fig. 11, gives an excellent view of the general health of the plants' conditions. Drones use scanning systems that cover large areas on pre-set routes. Computer vision is used throughout the production of these as well. Images are used for creating multi-spectral images

Table 7 Features of the studies dealing with the irrigation task in smart agriculture

Reference	Technology	Monitoring	Improvement/Limitation
Padalalu et al. [192]	Naive Bayes algorithm	Estimation of the precise amount of water and suggestion of the necessary fertilisers	Sensors data (humidity, soil temperature, and soil type (PH)) and weather forecasting sites
Perea et al. [193]	Decision Trees, Genetic Algorithm	Prediction of the irrigation events	Crop, Julian day, bank holiday, weekday, and climatic data (temperature, humidity, precipitation event)
Xie et al. [194]	Support Vector Regression method, Irrigation estimation algorithm and an optimisation model	Minimization of irrigation cost	Soil moisture information and cloudless irradiance, numerical weather information (cloud cover, humidity, precipitation) and solar energy data
Kokkonis et al. [195]	Fuzzy Neural Network algorithm	Management of irrigation	Soil moisture sensors
Goldstein et al. [196]	Gradient Boosted Regression Trees (GBRT), Boosted Trees Classifier (BTC), and linear regression models	The weekly irrigation plan prediction	Meteorological station data, actual irrigation records, historical sensor data
Goumopoulos et al. [197]	DM algorithms	Management of zone-specific irrigation	Sensor data (soil moisture, humidity, temperature, and other plant data)
Lamas [202]	Zigbee, LoRaWAN, and WiFi	Solar panel, agricultural monitoring	Agricultural monitoring system with energy harvesting
Han [203]	MATLAB	Soil and plant structures (soil porosity, tree branching, biochar porosity)	GUI-based application (for Windows OS)
Zaragoza [204]	REUTIVAR-App	Reclaimed water, irrigation, and fertilization management	It provides daily real-time irrigation and fertilization schedule recommendations at the farm scale
Jayaraman [208]	SmartFarmNet (Semantic Web Technologies)	Soil, fertilization, irrigation	Real-time data analytics, easy to use the e-commerce like use interaction model
Pereira [209]	Wemos Mini D1, Dg-2000 Ammonia Detector, DHT22, LDR, and MQ-137 electrochemical sensor	temperature, relative humidity, luminosity, and concentration of ammonia in the air	They proposed a prototype (a low cost, hardware, and software for monitoring)
Ramli [210]	LoRaWAN and IEEE 802.11ac	Crop, soil, temperature, and humidity	They proposed a reliable smart farm system
Deng [211]	RFID and LoRa	Temperature, moisture content, and chloride ion concentration of soil	They proposed a soil environment monitoring system based on RFID sensors and LoRa
Sai [212]	OASNDFA algorithm	Orange orchards	Sensor nodes deployed for measuring soil moisture and temperature
Pastor [213]	DCTA algorithm EC-5 and SHT-11 sensor	Orchid greenhouses	High and successful data delivery rate can be obtained through DCTA
Thakur [214]	Arduino, Python, Cloud, Soil Moisture and Passive Infrared sensor	Water, soil moisture	The proposed system provides smart irrigation and detection of intrusion
Anand and Perinbam [215]	Fuzzy Logic	Management of irrigation	Meteorological parameters
Mousa et al. [216]	Fuzzy Logic	Management of irrigation	Meteorological parameters

Fig. 11 Autonomous Mobile Robots used in Precision Agriculture **a** An Unmanned Aerial Vehicle, **b** Blue River Technology See-and-Spray Machine [219], **c** Agrobot Strawberry Harvester [219], **d** Autonomous Robot, **e** Agriculture Spraying Robot [220], **f** Agriculture Robot Use in Field, **g** Robotic Phenotyping [221], **h** Autonomous Agriculture Robot "Vinebot" [222], **i** Agricultural Robot, **j** Strawberry Harvesting Robot [223], **k** Robotic Apple Harvester [224], **l** Weed Removing Robot [225]

for crop analysis, plant monitoring, weed detection, and to determine if the disease is present and if plant health and drought is affecting crop productivity. When taking the total amount of potential yields into consideration, this is a reasonable estimate of the crop yield. More widely used robot applications include weed picking [217] and precision chemical application [218] employing machine vision.

Various different uses of drones and automated vehicles in smart agriculture are discussed in the following sub-section. It's a good match for greenhouse horticulture due to its low maintenance demands and controllable ecosystem. Environmental variability among crop parameters makes it difficult for traditional agriculture and environmental regulations to adjust to plant growth cycles. IoT sensors and actuators are proposed to control the environmental conditions for a specific kind of plant species. Artificial neural network (ANN) determines the conditions in the IoT cloud [226–228]. Waheed et al. [229] conducted a series of experiments in 2006 to classify hyperspectral imagery of experimental cornfields into categories of moisture stress, weediness, and nitrogen application rates using classification and regression trees (CART). A full spectrum analysis found that classification accuracy was 96% for the irrigation factor, 83% for the nitrogen, and 100% for the weed management methods. Additionally, both ANN [230] and SVM [231] are pattern recognition methods that may be used to handle hyperspectral data. Aqeel-ur-Rehman, in 2014 et al. [232] reviewed the applications of WSNs in agriculture and cited the necessity for sensors in this area. The major purpose of the authors' work was to implement sensors and networks for beneficial and productive solutions in agriculture. Keshtari and Deljoo [233] applied WSN to farming in 2012. Usually, WSNs are used for data collection, storage, collection, and data sharing. The primary goal is to be in tune with the real-time environmental properties of climatology and sensing data. High-quality remote monitoring and control for the design, construction, installation, and verification of a distributed WSN was the primary goal for this project.

Bhatnagar and Chandra [234] focused on soil health monitoring that shows the instantaneous reading of various parameters such as temperature, soil moisture, pH, and humidity in the screen of a farmer's smartphone. Dasig et al. [235] have discussed the implementation of IoT and WSN for precision agriculture in detail, emulating the advancement toward Agricultural 4.0. Yu et al. [236] have developed "Plant Spike," a low-cost, energy-efficient WSN system for soil health monitoring. Nurzaman et al. [237] used IoT for crop health monitoring and also to maximize agricultural output. AgriTalk, a cost-effective IoT platform, was designed and tested for turmeric cultivation in [238]. Goswami et al. [239] developed an IoT-based soil health monitoring system that monitors macronutrients N (Nitrogen), P (Phosphorus), K (Potassium), pH, soil moisture, and soil humidity. Authors in [240] designed and developed an IoT enhanced device—FarmFox, which can analyze the sensed information and transmitting it to the user via the internet. In [241], the researchers propose a holistic smart agriculture application that consists of various agricultural sensors, drones, and IoT hardware and software utilities. Table 8 gives some more state-of-the-art works on Iot and WSN in the smart agriculture domain.

2.1.8 Crop and Yield Management

Crop yield prediction is an essential task for the decision-makers at the national and regional levels (EU level) for rapid decision-making. An accurate crop yield prediction model can help farmers to decide on what to grow and when to grow. There are different approaches to crop yield prediction. The primary reason for farmers' concerns is the assumption that crop yields will be low, with the environmental parameters expected to have the most significant impact on the market. Like any other type of modeling, it can be characterized as a machine learning problem. Extensive research has been done on this subject. If yield mapping was done using an ML technique, it could be used in farms utilizing IoT information for yield surveillance through the old molecularly. Information collected will be used to provide data on land-use yields. In addition, ML systems, together with IoT, are utilized in agriculture to estimate and improve yields. There is a direct correlation between the Internet of Things and agriculture. Other works demonstrate that ML systems can be built on the IoT and can give real-time feedback [268, 269].

2.1.8.1 Crop Yield Prediction Using Conventional Data Mining Methods The authors in [270] proposed an improved multilayer perceptron (MLP) approach to predict the amount of sugar yield production in IoT agriculture. Experimental results show that the proposed MLP algorithm has maximum accuracy of 99%, the precision of 95%, recall of 96%, minimum mean absolute error (MAE) of 0.04%, and root mean square error (RMSE) of 0.006% for detecting sugarcane yield production. Tumer et al. [271] proposed a classification method to evaluate the process of crystallization syrup in sugar production using an artificial neural network. Kaburlasos et al. [272] presented a fuzzy-based approach to predict inclusion measure function for hellenic sugar industry (HIS). Elavarasan et al. [273] performed a survey of publications on machine learning models associated with crop yield prediction based on climatic parameters. Liakos et al. [274] discussed the application of machine learning in the agricultural sector. The authors in [275] performed a review study on determining the ripeness of fruits to decide the optimal harvest time and yield prediction.

2.1.8.2 Crop Yield Prediction Using Deep Learning Methods Table 9 gives some more state of artworks of deep learning in crop yield prediction.

Table 10 below offers some commercially available AI-based smart tools for precision agriculture and farming.

3 Discussions

Agriculture has faced considerable challenges such as a lack of irrigation systems, climate changes, groundwater density, food scarcity and waste, and much more. The reception of distinct cognitive solutions has a significant impact on the fate of cultivating. Despite the fact that large-scale research is still underway and some applications are now on the market, the industry remains underserved. Farming is still in its infancy when it comes to dealing with real-world difficulties and solving them with autonomous decision-making and predictive solutions.

It is pretty obvious that two activities must be completed in order to diagnose and classify a disease from a leaf: Image processing techniques such as pre-processing, segmentation, and others are first applied to the image samples, followed by machine learning approaches. The state-of-the-art research points that the Fuzzy K-NN was proven to be quite effective and accurate for nutrient deficit and potassium shortage in tomato leaves. SVM and CNN, on the other hand, outperform K-NN and random forest algorithms in terms of disease detection and categorization of tomato leaves. Bacterial spot,

Table 8 Example of IoT/AI applications in smart agriculture

Category	Tool/company	Description
Climate conditions Monitoring	allMETEO [242]	A portal to manage IoT micro weather stations, to gather real-time data access, and create a weather map. It also provides an API for easy real-time data transfer into developed or existing infrastructure
	Smart Elements [243]	A collection of products that improve efficiency by eliminating manual checking. They work by deploying a wide range of sensors generating a report back to an online dashboard, allowing rapid and informed decisions based on real-time conditions
	Pycno [244]	A software and sensor allowing continuous data collection and flow from the farm to smartphone. It also contains a dashboard to apply the latest phenological and disease models to monitor trends and assess the risk to agricultural products
Greenhouse automation	Farmapp [245]	A process of monitoring pests and diseases, generating reports for mobile applications. It records the data quickly and more efficiently than traditional methods (i.e., paper), allowing a smooth implementation. The stored data is synchronized with the server, enabling the following metrics to be immediately observed: (1) a satellite map with recorded points; (2) the current sanitary status of the farm; (3) comparative heatmaps to easily compare previous measures with the current situation; and (4) charts and reports concerning pests and diseases
	Growlink [246]	A platform that tightly integrates hardware and software products, enabling smarter working, including providing wireless automation and control, data collection, optimization, and monitoring and visualization
	GreenIQ [247]	A system to control irrigation and lighting from all locations and to connect IoT devices to automation platforms
Crop management	Arable [248]	A device that combines weather and plant measurements, sending data to the cloud for instant retrieval from all locations. It offers continuous indicators of stress, pests, and disease
	Semios [249]	A platform focused on yield improvement. It enables farmers to assess and respond to insects, disease, and the health of crops using real-time data, forming on-site sensing, big data, and predictive analytics solutions for sustained agricultural products
Livestock monitoring and management	SCR/Allflex [250]	An advanced animal monitoring system, aimed at the collection and analysis of critical data, including for individual animals. It delivers, when needed, the heat, health, and nutrition insights required by farmers for effective decision-making
	Cowlar [251]	A smart neck collar for monitoring dairy animals to gather information on temperature, rumination, activity and other behavior. The intelligence algorithm in the system allows for the detection of health disorders before the appearance of visual symptoms. It can monitor body movement patterns and gait to provide accurate oestrus detection alerts. It uses a solar power base unit, along with a waterproof and non-invasive monitoring system, both comfortable for the animal and requiring minimum maintenance
End-to end farm management systems	FarmLogs [252]	This system monitors field conditions, facilitating the planning and managing of crop production. It also markets agricultural products
	Cropio [253]	A decision-making tool used to optimize fertilisation and irrigation to control the amount of fertilizer and reduce the use of water. It combines weather information and satellite data to monitor crops and field forecasts
Predictive analytics	Farmshots [254]	A system analysing satellite and drone images of farms fields to map potential sign of diseases, pests, and poor nutrition. It turns images into a prescription map to optimise farm production and view analytics on-farm performance. Generated data in the cloud can be exportable into nearly all agricultural software for prescription creation
	aWhere [255]	A platform employed for weather prediction and information on crop sustainability. Its goal is to deliver complete information and insight for real-time agricultural decisions on a daily basis and at a global level

Table 8 (continued)

Category	Tool/company	Description
Crop and Soil Health Monitoring	Plantix [256]	A machine learning based tool to control and manage the agriculture process, disease control, and the cultivation of high-quality crops
	Trace Genomics [257]	A soil monitoring system performing complex tests (i.e., DNA) on soil samples
Agriculture machines/drones	SkySquirrel [258]	A drone system aimed at helping users to improve their crop yield and reduce costs. Users pre-program a drone route, and, once deployed, the device will leverage computer vision to record images to be used for analysis. Once the drone completes its route, users can transfer the data to a computer and upload it to a cloud drive. It uses algorithms to integrate and analyse the captured images and data to provide a detailed report on the health and condition of crops
	See and Spray [259]	A robot designed to control weeds and protect crops. It leverages computer vision to monitor and precisely spray weeds and infected plants
	CROO [260]	A robot that assists in the picking and packing of crops. The manufacturer claimed that this robot can harvest eight acres in a single day and replace the work of thirty human labourers
Weather risk	Arable [261]	Offers an in-ground monitor that collects and analyses 14 data about weather patterns, crop health, and soil quality
	Farmers Edge [262]	Provides farm management software that collects and analyses data from satellites, weather stations, as well as farm equipment. Using image processing and analytics, farmers are able to make data-driven decisions about crop planting, cultivation, and harvesting
	Prospera [263]	Autonomous crop management solution that leverages their exist- 15 ing algorithms to not only provide recommendations to growers but also directly control center pivots
	Blue River Technology [264]	Produces a machine that attaches to an existing tractor and precisely detects and applies herbicide to remove unwanted weeds from fields while avoiding crops
	FarmBot [265]	Open-source robotics project that consists of a Cartesian coordinate machine that uses software to automatically plant seeds, detect and control weeds, and water plants
	Plantix [266]	Has built up the world's largest database of plant diseases and uses image recognition and deep neural networks to identify the plant type as well as possible disease, pest, or nutrient deficiency
	FFRobotics [267]	Uses deep learning algorithms to identify the fruit, determine ripeness, and send a linear robotic arm to harvest the fruit

early blight, late blight, leaf mold, septoria spot, spider mite, healthy, target spot tomato mosaic virus, and tomato yellow leaf curl virus were all detected with 99.25% accuracy by the CNN. In addition, the PlantVillage dataset was the most commonly utilized dataset for training in most of the current research work in the literature linked to the categorization of illness and infected tomato leaves. Pretrained transfer learning techniques, such as AlexNet architecture, might be an easy alternative for not only obtaining high detection accuracy but also saving both expenses and coding labor in the identification of potato leaves. CNN has the highest accuracy of 98.33% among the available classifiers, followed by BPNN, MSVM, ANN, SVM, and RF techniques. Deep learning models such as DCNN performed admirably, while machine learning approaches such as MSVM, ANN, SVM, and RF also performed admirably. Various existing works had captured real photographs for their rice illness diagnosis. In detecting and categorizing illnesses in paddy leaves, CNN-based models have reached the highest level of accuracy.

The use of deep learning in the field of agricultural disease picture recognition has yielded a number of significant results. Deep learning approaches, on the other hand, are primarily data-driven, rendering them vulnerable to the following drawbacks:

- The training process is prone to over-fitting in the absence of large-scale labeled training sets, making it challenging to develop an optimum model.
- The number of parameters in the model grows exponentially as the complexity of the models grows, limiting their generalizability.
- The models must be trained from scratch for each new dataset and task, increasing the hardware requirements

Table 9 A summary of the works of optimal crop yield in the smart agriculture context

References	Target	Model Used
Schwalbert et al. [276]	Satellite-based soybean yield forecast: Integrating machine learning and weather data for improving crop yield prediction in southern Brazil	Long-Short Term Memory (LSTM)
Chu and Yu [277]	An end-to-end model for rice yield prediction using deep learning fusion	The combination of Back-Propagation Neural Networks (BPNNs) and Independently Recurrent Neural Network (IndRNN)
Reddy and Kumar [278]	Crop Yield Prediction (CYP) using various deep learning techniques	Convolutional Neural Networks (CNN), RNN
Elavarasan and Vincent [279]	Foreseeing the crop yield depending on climate, soil, and water parameters	Deep belief network (DBN) and fuzzy neural networks system (FNN)
Forsythe et al. [280]	Crop yield prediction using deep neural networks to increase food security in Senegal, Africa	CNN-LSTM Model
Jeong et al. [281]	Scalable rice yields from a crop model using targetted deep learning techniques	LSTM and 1D-CNN
Haque et al. [282]	Deep Neural Networks in crop yield	Deep Neural Networks (DNN)
Nosratabadi et al. [283]	Crop yield prediction models based on hybrid machine learning method	Artificial neural networks-imperialist competitive algorithm (ANN-ICA) and artificial neural networks-gray wolf optimizer (ANN-GWO)
Zhou et al. [284]	Strawberry Yield Prediction Based UAV and Near-Ground Imaging on a Deep Neural Network	You Only Look Once (YOLOv3)
Sharma et al. [285]	Method to predict wheat crop yield in India from publicly available satellite imagery	DCCN
Khan et al. [286]	Use Of Deep Neural Networks For Fruit Yield Prediction	Scale conjugate gradient backpropagation (SCG)
Qiao et al. [287]	Crop Yield Platform from multi-spectral images	SSTNN (Spatial-Spectral-Temporal Neural Network), combining 3D convolutional and recurrent neural networks
Xu et al. [288]	Large-scale and small-scale cotton yield prediction	Bayesian regularization BP (backpropagation)
Tello and Ko [289]	Spring wheat (triticum aestivum) yield a prediction process using multispectral images	The combination of Convolutional Neural Networks and Long-Short TermMemory (CNN-LSTM)
Wolanin et al. [290]	Estimating and understanding crop yields with explainable deep learning in the Indian Wheat Belt	Convolutional Neural Networks (CNN)
Bhojani and Bhatt [291]	Wheat crop yield prediction using new activation functions in neural network	Deep Neural Networks (DNN)
Fathi et al. [292]	Crop Yield Prediction Using Deep Learning in Mediterranean Region	Deep Neural Networks (DNN)
Shidnal et al. [293]	Crop yield prediction: two-tiered machine learning model approach	Convolutional Neural Networks (CNN)
Bolton and Friedl [294]	Predicting maize and soybean yield in the Central United States	Deep Neural Networks (DNN)
Nguyen et al. [295]	Spatial–Temporal Multi-Task Learning for Within-Field Cotton Yield Prediction	Spatial–Temporal Multi-Task Learning
De Alwis et al. [296]	Duo Attention with Deep Learning on Tomato Yield Prediction and Factor Interpretation Duo Attention	Long-Short Term Memory
Jiang et al. [297]	A deep learning approach to conflating heterogeneous geospatial data for corn yield estimation: A case study of the US Corn Belt at the county level	Long-Short Term Memory (LSTM)
Saravi et al. [298]	Quantitative model of irrigation effect on maize yield by deep neural network	Deep Neural Networks (DNN)

Table 9 (continued)

References	Target	Model Used
Kang et al. [299]	Comparative assessment of environmental variables and machine learning algorithms for maize yield prediction in the US Midwest	Long-Short Term Memory (LSTM) and Convolutional Neural Networks (CNN)
Zhang et al. [300]	Combining Optical, Fluorescence, Thermal Satellite, and Environmental Data to Predict County-Level Maize Yield in China Using Machine Learning Approaches	Long-Short Term Memory (LSTM)
Wang et al. [301]	Combining Multi-Source Data and Machine Learning Approaches to Predict Winter Wheat Yield in the Conterminous United States	Deep Neural Networks (DNN)
Ju et al. [302]	Machine learning approaches for crop yield prediction with MODIS and weather data	Long-Short Term Memory (LSTM) Convolutional Neural Networks (CNN), Stacked-Sparse AutoEncoder (SSAE)
Yalcin [303]	An Approximation for A Relative Crop Yield Estimate from Field Images Using	Deep Learning Convolutional Neural Networks (CNN)
Wang et al. [304]	Deep Transfer Learning for Crop Yield Prediction with Remote Sensing Data	Long-Short Term Memory (LSTM) for Transfer Learning
Shook et al. [305]	performance records from Uniform Soybean Tests (UST) to dissect and predict genotype response in multiple-environments	LSTM, RNN
Gomez et al. [306]	Wheat yield production	PLSR, ANN, RF
Aplolo et al. [307]	Maize	DNN
Shekoofa et al. [308]	Determining the most critical physiological and agronomic traits contributing to maize grain yield through machine learning algorithms: A new avenue in intelligent agriculture	Decision tree, clustering
Kunapuli et al. [309]	Yield prediction for precision territorial management in maise using spectral data	Polynomial regression, logistic regression
Ahamed et al. [310]	Applying data mining techniques to predict the annual yield of major crops and recommend planting different crops in different districts in Bangladesh	Linear regression, neural networks, clustering, k-nearest neighbor
Pantazi et al. [311]	Wheat yield prediction using machine learning and advanced sensing techniques	Neural networks
Mola-Yudego et al. [312]	Spatial yield estimates of fast-growing willow plantations for energy based on climatic variables in northern Europe	Gradient boosting tree
Everingham et al. [313]	Accurate prediction of sugarcane yield using a random forest algorithm	Random forest
Ying-xue et al. [314]	Support vector machine-based open crop model (SBOCM): Case of rice production in China	Support vector machine
Cheng et al. [315]	Early yield prediction using image analysis of apple fruit and tree canopy features with neural networks	Neural networks
Ali et al. [316]	Modeling managed grassland biomass estimation by using multitemporal remote sensing data machine learning approach	ANFIS, neural networks, multiple linear regression
Kouadio et al. [317]	Artificial intelligence approach for the prediction of Robusta coffee yield using soil fertility properties	Extreme learning machine, multiple linear regression, random forest
Bi and Hu [318]	Applying machine learning for Crop Yield Production	Genetic algorithm (GA)-assisted deep learning

and computational cost and potentially limiting their practical applicability.

Transfer learning may take models taught in one domain and apply them to another, resulting in high-quality model learning and creation on the basis of minimal amounts of data. This strategy avoids the drawbacks of deep learning techniques, such as their reliance on vast volumes of labeled training data. When faced with low data resources, transfer learning is particularly well suited for agricultural disease picture recognition.

Applications must be more resilient in order to explore the vast potential of AI in agriculture. Only then would it be capable of handling frequent changes in external conditions, facilitating real-time decision making, and utilizing a suitable framework/platform for efficiently collecting contextual data. Another significant factor is the high expense of many cognitive farming technologies available on the market. To ensure that technology reaches the masses, solutions must become more affordable. The solutions would be more economical if they were built on an open-source platform, leading to faster acceptance and higher penetration among farmers. Farmers will benefit from the technology since it will help them achieve higher yields and a more consistent seasonal harvest. Artificial intelligence, from detecting pests to predicting which crops will yield the best returns, can help humanity meet one of its most pressing challenges: feeding an additional 2 billion people by 2052, despite climate change disrupting growing seasons, turning arable land into deserts, and flooding once-fertile deltas with seawater. Farmers in many nations, including India, rely on the monsoon for their crops. They are primarily reliant on weather forecasts from several departments, particularly for rain-fed agriculture. AI will be useful in predicting weather and other agricultural circumstances such as land quality, groundwater, crop cycle, and pest assault, among others. These sensors have a lot of potential in agriculture. Data such as soil quality, weather, and groundwater level, among other things, can be derived by agriculture scientists and used to optimize the cultivation process. In order to collect data, AI-enabled sensors can be integrated in robotic harvesting equipment. It's been suggested that AI-based advisories could help enhance productivity by 30%. The most difficult aspect of farming is crop damage caused by natural disasters, such as pest attacks. The majority of the time, farmers lose their crops owing to a lack of sufficient information. In this cyber age, technology might be beneficial to farmers in protecting their crops from cyber-attacks. Many businesses have adopted this strategy. Such operations have shown to be helpful in the past, providing motivation to develop a system to monitor and safeguard crops. NatureFresh Farms, a 20-year-old company that grows veggies on 185 acres between Ontario and Ohio, is developing and researching the technique. Knowing

Table 9 (continued)

References	Target	Model Used
Taherei Ghazvinei et al. [319]	Sugarcane growth prediction based on meteorological parameters using extreme learning machine and artificial neural network	Neural networks
Xu et al. [320]	Design of an integrated climatic assessment indicator (ICAI) for wheat production	Random forest, support vector machine
Ranjan and Parida [321]	Paddy acreage mapping and yield prediction using sentinel-based optical and SAR data in Sahibganj district, Jharkhand (India)	Linear regression

Table 10 Commercially available Artificial Intelligence (AI)-based tools for smart agriculture

Company	Website	Products/service
AGEYE Technologies	https://ageyetech.com	AI-powered platform for indoor farming
aWhere	http://www.awhere.com	Weather information with machine learning algorithms in connection with satellites to predict the weather, analyze crop sustainability, and evaluate farms for the presence of diseases and pests
Blue Reiver Technology	https://bluerivertechnology.com	Smart farm machines to manage crops at a plant level and protect crops from weeds
FarmShots	http://farmshots.com	Integrated scouting and variable rate prescription platform for farmers based on images captured by satellites and drones
Fasal	https://fasal.co	AI-based solutions for the small farmer to provide critical parameters using affordable sensors
Harvest CROO Robotics	https://www.harvestcroorobotics.com	Robot system to pick and pack vegetables
HelioPas AI	https://www.heliopas.com irrigation, fight mildew and deal with drought	AI-based soil moisture monitoring system to control
Hortau Inc	https://hortau.com	Web-based irrigation management service Ibex
Automation	http://www.ibexautomation.co.uk	Autonomous agricultural robot systems for farmers, including an autonomous precision weed detection and spraying system
PEAT	https://plantix.net	Deep Learning-empowered image recognition application to identify potential defects and nutrient deficiencies in soil
Root AI	https://root-ai.com	AI-based automated and robotic solutions for indoor farmers
Trace Genomics	https://www.tracegenomics.com	Soil analysis system to provide a sense of soil's strengths and weaknesses using machine learning
VineVIew	https://www.vineview.com	Highly specialized aerial-based spectral sensors and a cloud-based image processing service to monitor crop health

how many tomatoes will be available to sell in the future makes the sales team's job easier and benefits the bottom line directly. According to data from prominent universities, there is a significant amount of food waste around the world, which may be addressed with the correct algorithms, which will not only save time and money but also lead to long-term development.

4 Challenges and Future Scope of Data Mining in Smart Agriculture

A wide range of challenges applies to the gathering, processing, and making use of data for agricultural productivity. One of the significant issues that farmers have to face in order to thrive in the age of information is data security and ensuring privacy. Data availability and quality problems are frequently found in agricultural information systems. When there is more data in real-time, this gets much more complicated. Data efficiency and spatial semantic integration are often a struggle when it comes to data mining.

4.1 Challenges

The applications of machine learning and deep learning in the field of agriculture are huge, with many challenges.

4.1.1 Privacy

The agricultural information contains their personal data (identity, geographical location, financial data, entrepreneurial knowledge, etc.). Most farmers who have their information made available through digital platforms will be unaware of what it says about them. True, farmers are unaware that their personal information is being gathered and used, and even more worrisome, what it is being used for. Data mining provides organizations with the opportunity to focus on people to accumulate and collect enormous amounts of information about farmers, which could be enough to create and analyze a personality or psychological portrait of the subjects. Even if this data could be misused, there is the danger that it will injure his reputation or just get discovered and fall into the wrong hands. This could also make it difficult for him to carry out his normal activities. They need to be reassured that their data will be used to develop creative ideas but not for competitive advantage. Data mining can make it difficult for farmers to keep their personal information private. Privacy and confidentiality policies require substantial time and resources to implement.

4.1.2 Available Databases and Size Issue

It is difficult to obtain leaf images for specific plant infections. Due to this fact, the sizes of the available plant data sets are very small. Only limited works have reported thousands of images for research purposes. Due to the small database size problem, a large portion of the data set is used for the training phase in most of the deep learning methods. Furthermore, the available database images are collected in very constrained environmental conditions. We believe that images must be gathered in real-world conditions to make the algorithms more practical. Efficient image acquisition of leaf images is the need of the hour. If these images are captured in real-time scenarios, such databases would be warmly welcomed in the research community. From this survey, it is observed that many researchers use data source sites like Kaggle, Meandly, IEEE Dataport, etc., to get the data to build models. If the required data is not available then researchers need to build their own dataset.

4.1.3 Quality and Precision of Data

A lot of data needs to be gathered and transformed into information if we want to succeed in agriculture. Traditional analytical tools have been ineffective against the sheer weight of this new data. Crop management will be vastly improved with the use of data mining analysis. Excellent data quality is needed to get helpful information from the DM process. Agricultural data usually comes from different databases and models and is thus messy, as well as the presence of many missing pieces. Data collected through these systems is missing, has lots of problems and inconsistencies. There is significant work that needs to be done before the data can be processed in the data mining process. Providing data for models can face a number of obstacles and challenges such as uncertainty, indefinite persistence, and incapability, and therefore calls for data processing (geographical and temporal). Using more data is inevitable. Accordingly, both syntax and semantics must be harmonized to guarantee data portability in a (definitions). Better data handling allows all kinds of new kinds of analysis and product development. Reliability is a major concern for IoT devices in terms of data transmission. Devices need to gather and transfer reliable data in order to make appropriate decisions when necessary. False reading will greatly reduce system reliability.

4.1.4 Unnecessary Noise and Background in Crop's

The technique of image segmentation is utilized to retrieve the infected section from an image. When the image background comprises colors other than white and black or other features such as plants, leaves, dirt, grass, and so on, extracting the contaminated leaf segment from an image becomes difficult. If farmers want to diagnose crop illnesses in real-time from the fields, the photo may have a lot of background features. As a result, the system must be able to remove all extraneous elements from the image so that just the desired segment remains.

4.1.5 Image Capture Conditions

The images in all available datasets were recorded in a controlled environment in laboratories, and in other cases, images were generated utilising animation techniques, according to the literature. Consider what happens if a farmer or capturing equipment in the field tries to catch the same thing at different times of the day. Because of many variable characteristics such as different light intensity, dampness, and other environmental factors, it is difficult to acquire a similar image in that circumstance. As a result, photographs of the same leaf must be captured from several perspectives, at various times, and under various climatic circumstances.

4.1.6 Issues with Available Feature Extraction Methods

Preprocessing, feature extraction, and segmentation are all important steps in constructing a machine learning-based system. The type of data collection plays a role in determining the best preprocessing and segmentation strategy. The technique that is best suited for a certain acquisition is usually the one that is used. We've seen a lot of variation in the algorithms that have been published so far across different modules.

4.1.7 Difficulties in Classification Module

For a long time, plant disease automation and detection have been a hot topic of research. Researchers claim highly acceptable results despite using very few photos for training and testing. Researchers in this field are looking into a variety of classifiers. According to the findings, backpropagation neural networks, SVM, and discriminant analysis (especially linear) outperform the competition. After that, Nave Bayes, random forest, nearest neighbor, and multilayer perceptron are used. However, newly established optimized deep neural networks significantly improve state-of-the-art outcomes. Deep convolutional neural networks can assist improve the outcomes for enormous data sets if they are used more effectively.

4.1.8 Evaluation Measures

There are a variety of metrics that can be used to compare different classification algorithms. True-positive (TP) refers to the number of infected samples that were correctly recognized; true-negative (TN) refers to the number of healthy photos that were correctly detected. False-positives (FPs) are a measure of the number of healthy samples that were mistakenly identified as infectious. Finally, false-negative (FN) samples are infected samples that were mistakenly classified as healthy. The ratio of correct classifications (TP + FP) to total classifications (TP + FP + TN + FN) is known as accuracy. The ratio of correctly recognized samples as infected (TP) to the total samples identified as infected is known as precision (sum of TP and FP). Similarly, recall is the ratio of TP to the actual number of infected samples (sum of TP and FN). Lastly, F-measure represents the harmonic mean of precision and recall.

4.1.9 Concerns on devices

Device standardization is necessary to ensure that technology may be used in a wide range of applications. However, there are no data-processing standards formats. And the misreading of the mismatched code can result in different outcomes. Machine standardization can help to resolve system, application, equipment, and product interoperability difficulties. Furthermore, the development of the 5G network has made communication between devices and servers 100 times faster than it was with 4G. 5G is a suitable technology for sending data from remote sensors because it can transport substantially more data. As a result, the adoption of 5G as a new communication network is required to meet the needs of more secure users and faster data transfer rates. One of the most serious issues is a lack of interoperability.

4.1.10 Spatial Data Importance

The overall goal of smart agriculture is to manage environmental impacts and maximize profit. Conventional data mining approaches are typically designed for relational databases but are not entirely applicable to geographically dispersed data. For smart farming, new data mining methods are required to take into account spatial and temporal correlations in the data.

4.1.11 Incorporation of Agricultural Domain Knowledge in Data Mining

Agriculture is an interdisciplinary field that encompasses a variety of subjects, including environmental sciences, agronomy, soils, etc. The data we use in a data mining project can come from various sources. Due to the sensor and high data throughput, new challenges arise, particularly operable semantics: figuring out how to keep the meaning of data and correctly representing it over time? The problem of integrating domain knowledge is one of the most challenging problems in data mining. It can be thought of as a form of fusion of agriculture, making agricultural domain knowledge compatible with data mining research.

4.1.12 Scalability of Data Mining algorithms

Smart agriculture is responsible for generating enormous amounts of data as a result of all the various gadgets in use. Heterogeneous data, in particular, is being produced by remote sensors. They will probably have a large data set, which will allow them to demonstrate the real relationships. Data mining algorithms, however, face the constant requirement of needing to make countless decisions in the agricultural sector: Can they handle the volume of data quickly. Data mining algorithms need to be scalable with exponential search problems to search through these large data sets. The development of parallel and distributed algorithms are of critical importance in agricultural data mining.

4.1.13 Drones

Because the drone can only fly for an hour or less, the flight line path must be set with the overlap between the flight lines in mind. Drones are expensive, especially those with high-resolution cameras and thermal cameras, as well as good software, hardware tools, and devices. Drone operations require licences, which can be challenging in many nations, as well as the height not exceeding 400 feet. Climate conditions have an impact on drone operation. Wind speed and wetness have an effect on drone operation; thus, the weather should be considered before beginning work.

There are a few extra challenges to be aware of:

(1) Identifying the problem and understanding the business need.
(2) Gaining a better understanding of the consumer and how they engage with technology.
(3) An application that is easy to use.
(4) Model performance in real-world circumstances.
(5) Model power consumption and battery restrictions for running the model on devices.
(6) Camera configurations at the user end for computer vision models.

Following are a few recommendations based on the results of this in-depth study to make the implementation process more efficient, accurate, seamless, and deployable.

(1) Concentrate on developing a machine learning model to address a specific problem, such as classification or recommendation.
(2) Create your own dataset for training the model and make it available to other researchers via open platforms such as Kaggle, Meandly, IEEE Dataport, and so on.
(3) Use publicly available datasets for model testing and validation.

(4) Use "Transfer Learning" approaches to shorten the time it takes to train a model.
(5) AutoML is a cutting-edge method for creating more accurate, high-quality machine learning models in less time.
(6) It is advised that the model be deployed in a real-time application to assist the intended users.

4.2 Future Scope

The following paragraphs describe some elements that may help to improve and enhance the current state-of-the-art and provide researchers with some prospective ideas for future research:

4.2.1 Disease Stage Identification

One of the most critical aspects of plant disease identification is disease stage identification. There are various stages to each disease. The majority of the researchers concentrated their efforts on disease type identification, but none of them focused on disease stage identification. Furthermore, such systems must be able to recommend specific measures based on the stage of the disease. Disease forecasting will aid agriculturists in taking the appropriate activities and precautions to limit the percentage of damage.

4.2.2 Quantification of a Disease

The quantification of a certain disease is another intriguing subject to investigate. Despite the fact that significant research has been done in this area, only a few researchers have determined the extent of the disease's impact. They can be quite beneficial since corrective steps can be implemented based on the severity of the sickness. This type of quantification will discover the fraction of a culture that is infected with a disease. Because the number of pesticides can be managed, this study perspective is critical. Normally, farmers use chemicals to treat diseases without first analyzing or quantifying them. Such behavior is exceedingly hazardous to human health. Developing an effective image processing application will aid in determining whether or not specific chemicals are required.

4.2.3 Mobile and Online Applications

Several solutions for disease identification applications have been presented in the literature. However, just a few of the portals and mobile apps are publicly published and accessible via the internet. Assess Software and Leaf Doctor are two of these applications, both of which are free to use. These programs, on the other hand, function with photographs that have a flat, black background. As a result, such online systems and apps are critical for identifying plant diseases. The availability of technologies like this will aid farmers in identifying a specific illness. Such software can be used to generate analysis reports, which can then be sent to a disease expert for advice.

4.2.4 Exploring Transfer Learning to Increase Data Size

Similarly, current tendencies in CV development, which are rapidly going toward DL approaches, are not very promising for plant disease diagnosis. Given the difficulty of the data, particularly at the training stage, transfer learning is the best choice to consider. A heterogeneous domain strategy can be used to investigate knowledge transmission. LSTMs, optical flow frames, temporal pooling, and 3D convolution are some of the keywords that might be explored in terms of automatic plant disease identification. Last but not least, better and more thoroughly constructed methodologies are required for further research in this area. The case of data augmentation, for example, might be examined further.

4.2.5 Incorporating New Technologies in Agriculture

Agri-food supply chain traceability requires more attention and has significant IoT potential. Meanwhile, the most commonly utilised IoT communication technologies in these publications are LoRa, ZigBee, and WiFi, while emerging high-speed communication technologies such as 5G and NB-IoT are expected to be widely used to enhance agricultural production modernization and intelligence. With the advancement of current technology, there is a lot of room for IoT-based agriculture to develop new and effective solutions. Low-cost systems with advantages such as autonomous operation, low maintenance, energy efficiency, ease of use, and sturdy architecture are, particularly in demand.

5 Conclusions

The value of artificial intelligence is widely recognized across a wide range of industries, including agriculture. A segment of technologies in the agricultural sector is becoming crucial to business survival. Data lies at the heart of farming decisions, and the potential is enormous. More importantly, ML is expected to be a source of greater resource efficiency in sustainable resource utilization and an enabler of massive environmental benefits. This technology can make a significant difference in agriculture if stakeholders in the process see it, have a different attitude towards it, and funding can be found. The agricultural industry has a number of concerns, including a lack of appropriate irrigation systems, weeds, crop yields, plant monitoring issues owing to crop height, and extreme weather conditions. However, with the help of technology, performance may be improved, and thus these issues can be resolved. It can be improved with AI-driven techniques such as remote sensors for detecting soil moisture content and GPS-assisted automated irrigation. Farmers' difficulty was that precision weeding techniques were able to offset the high amount of crops lost during the weeding procedure. The self-driving robots not only increase productivity but also cut the use of unneeded pesticides and herbicides. Aside from that, farmers may use drones to successfully spray pesticides and herbicides on their farms, and plant monitoring is no longer a hassle. For starters, in agriculture difficulties, man-made brain power can be used to understand resource and job shortages. In traditional tactics, a significant amount of labor was necessary to get agricultural parameters such as plant height, soil texture, and content, which necessitated manual testing, which was time-consuming. Quick and non-damaging high throughput phenotyping would be possible with the help of the various systems investigated, with the added benefit of flexible and favorable activity, on-demand access to information, and spatial goals.

In this paper, we have discussed how ML in general and DL, in particular, have helped identify the diseases in plants, optimal irrigation, pesticides control, crop phenotyping, and improved crop yield. If the diseases are not correctly identified, they affect the crop yield and ultimately result in long-term issues, such as global warming and even famine. It can be deduced from the studies that with precision farming, more pragmatic farming may be carried out utilizing scientific methodologies such as remote sensing, GPS, data analytics, and so on, resulting in increased agricultural productivity and reduced potential environmental damage. In addition, the abnormality can be recognized in the plant at an early stage using image recognition software, artificial neural networks, and a variety of other technologies. Because there are so many different types of crop diseases and so few datasets, fine-tuning models that have been pre-trained on large-scale public datasets like PlantVillage and ImageNet to be able to do image recognition on the basis of few samples is desirable. It can be demonstrated that these methods can reach great levels of accuracy when performing plant disease image detection when they are based on large-scale open-source datasets and pre-trained models. However, further research revealed that the scale of the plant image collection used for modeling, as well as the context in which the photos were obtained, might have a significant impact on recognition accuracy. The recognition accuracy of systems built using the PlantVillage dataset is more remarkable since most of the photos in the dataset were captured with a simple background or in a laboratory environment with less interference.

Declarations

Conflict of interest The authors declare that there are no competing interests regarding the publication of this paper.

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