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R Wongamthing
Ph.D. Scholar, Department of Plant Pathology, College of Agriculture, Vellanikkara, Kerala Agricultural University, Thrissur, Kerala, India

Chandana HS
Ph.D. Scholar, Division of Genetics, ICAR-Indian Agricultural Research Institute, New Delhi, Delhi, India

Akash Yadav
Senior Research Fellow, ICAR - Indian Grassland and Fodder Research Institute, Jhansi, Uttar Pradesh, India

Divyanivedita Pradhan
M.Sc. (Agri.) Scholar, Faculty of Agricultural Sciences, Soa University, Odisha, India

Umesh Thapa
Professor, Department of Vegetable Science , Faculty of Horticulture, Bidhan Chandra Krishi Viswavidyalaya, Nadia, West Bengal, India

Anjali Verma
Ph. D (Agri.) Scholar, Department of Plant Pathology, Banda University of Agriculture and Technology,

Yumkhaibam Sonia Shahni
Ph.D. Scholar, Department of Plant Pathology, SAS, Nagaland University, Nagaland, India

Preetilagna Dhal
Assistant Professor, Department of Vegetable Science, Faculty of Agricultural Sciences, Siksha O Anusandhan University, Bhubaneswar, Odisha, India

PT Sharavanan
Associate Professor, Department of Plant Pathology, Centre of Excellence in Millets, Tamil Nadu Agricultural University, Athiyandal, Tamil Nadu, India

Corresponding Author:
R Wongamthing
Ph.D. Scholar, Department of Plant Pathology, College of Agriculture, Vellanikkara, Kerala Agricultural University, Thrissur, Kerala, India

Transforming agriculture with artificial intelligence: Methods, applications and limitations for diagnosing plant diseases

R Wongamthing, Chandana HS, Akash Yadav, Divyanivedita Pradhan, Umesh Thapa, Anjali Verma, Yumkhaibam Sonia Shahni, Preetilagna Dhal and PT Sharavanan

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Abstract
The importance of accelerating the understanding of biology and ecology is widely recognized. Agricultural systems are of special importance due to their role in providing food, fiber, and energy, and it is believed that their strategic importance has increased and will continue to increase. The use of artificial intelligence in agricultural systems is also not new. For example, the agriculture industry has been known to use expert systems in production since the 1990s. Since then, we have seen a series of works that propose new uses for this technique. But even with this breeding of new techniques and their applications, there are still an extensive number of open opportunities and big questions yet to be easily answered using artificial intelligence. This paper directly addresses several of these questions, focusing on plant health management and considering each of the questions addressed as distinct works.

Keywords: Biology and ecology, agricultural systems, food, fiber, and energy

Introduction
Agriculture transformations have revolutionized crop management practices over recent years. Numerous studies predict the growth of the role of information technologies in agriculture in the future, which will enable farmers to obtain comprehensive data about soil conditions, moisture, mineral and nutrient concentration, light, pressure, temperature, weather forecasts, etc. This data will be used to define and apply optimal treatment schemes (e.g. liquor and fertilizers amounts, sowing and harvesting time, etc.) for each field zone. In addition, the systems of indirect crop management monitoring, which rely on Remote Sensing (RS) solutions, are actively applied. The RS data includes satellite, aerial, and unmanned aerial vehicle photographs detecting the Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Plant Phenotyping Index (PPI), and other vegetation indices, which allow obtaining information about vegetation status (Aljaloud *et al*., 2022) [1].

An important issue in crop management is the timely detection of diseases, the consequences of which can be very severe (e.g. weed, fungi, insects). As a result, application of the treatment (e.g. herbicides, fungicides, insecticides) is irrelevant or slows the malfunction (e.g. soil erosion, crop loss, etc.). It is essential to detect crop diseases in the earliest stages (One-day duration) before the visible symptoms appear. The application of precision methods requires the development of expert systems based on Artificial Intelligence (AI) tools, which can ensure planned actions or detect diseases in the lowest class in the absence of a reliable decision (Sykes *et al*., 2023) [9].

Background and Significance
Even after being cultivated for decades, certain diseases on plants continue to challenge scientists, cultivators, and farmers due to a wide range of complex symptoms that depend on different pathogens, climate, soil type, varietal tolerance, and more. Hand-written record-keeping and assessment of these diseases are cumbersome and time-consuming tasks, often leading to peer-to-peer communication issues in recognizing and noting the disease.

For centuries, farming was hailed as the most noble profession. People took great care of seeds and saplings so that they would get the best yield. But, with changing times, most agriculture has been industrialized, with rampant misuse of antibiotics, thick fertilizers, and pesticides to get maximum yield, regardless of future repercussions. To keep diseases and pests at bay, this practice has continued since the pre-industrial era. Sadly, this contaminated the food chain so severely that people have begun to suffer from serious diseases like cancer, kidney failures, and skin allergies. To reduce the growing cases of such ailments, organic farming has gradually gained attention over the past ten years (Olubusola *et al*., 2024) [8]. After years of oblivion, agriculture and the farmer have become the limelight of global business investment, with the most powerful nations attempting to increase their share in foreign farming. Unfortunately, the majority of farmers are not aware of where to start and what steps to undertake, and as a result, they begin losing their produce to agricultural diseases, insects, nematodes, and fungi. Due to a lack of scientific methods of disease identification and control, farmers tend to use toxic pesticides instead (Yao *et al*., 2023) [16]. Currently, the world is moving towards modern diagnostics. Elements of Information Technology (IT) like Cyber-Physical Systems (CPS), the Internet of Things (IoT), Intelligent Agents, and other such precepts can facilitate the creation of smart agricultural systems that would assist farmers in efficient monitoring and control of other fields, thus escaping the losses caused by insects, diseases, and viruses. Computer vision-based monitoring of plants to identify diseases, pests, and fungi would be of primal importance for timely remediation, intervention planning, and control measure proposals. Approaches would also need to be developed to forecast outbreaks of diseases or infections created by unforeseen climate changes. The article explore the various methods, applications, limitations, and future prospects of artificial intelligence in diagnosing phytopathological diseases. By examining the current state of knowledge seeks to identify the gaps and areas of improvement in current research and present the likely future directions for advancing this field (Olubusola *et al*., 2024) [8].

A comprehensive overview of the methods used in diagnosing diseases through traditional and artificial intelligence techniques is provided. Factors that cause a curtailment in the scope of traditional techniques and how artificial intelligence can address these curtailments are explained. Furthermore, the important machine learning platforms and strategies necessary for integrating artificial intelligence into agriculture are discussed. The applications and importance of artificial intelligence methods in agriculture, including the prevention of crop losses caused by diseases, prevention of resource wastage, and maximization of yields through precision agriculture, are highlighted. The various artificial intelligence tools that have been developed for the detection of phytosanitary diseases in agriculture are also discussed. Finally, the existing limitations and future improvements of each method related to agriculture are elucidated (Aljaloud *et al*., 2022) [1].

Artificial Intelligence in Agriculture

Artificial Intelligence (AI) refers to the ability of human-made machines or systems to complete actions typically requiring human intelligence. These actions can include reasoning, understanding language, visual recognition, categorization, prediction, and decision making, among others. The term "Artificial Intelligence" was first coined in 1956. Since then, AI has changed drastically, particularly in the last 20 years, due to parallel advances in hardware and the growth of the internet (Chen *et al*., 2023) [2]. In agriculture, research efforts have focused on a wide variety of applications currently widely used in farm settings like automated harvesting, disease and weed detection, and soil mapping using drones. All these applications might potentially redefine farming practices.

There are many potential benefits of AI in agriculture. Higher crop yields adjacent to healthier crops and improved sustainability are some of the benefits sought daily by farmers, breeders, and researchers (Aljaloud *et al*., 2022) [1]. Moreover, cost-saving plus=adverse effects from pesticides, fertilizers, and herbicides used exclusively or inefficiently are needed to preserve the environment and future agricultural productivity. Adopting AI technologies also implies an increased responsibility on part of farmers, researchers, and agricultural service providers. In this regard, farmers need to understand how the provided data is used and how future changes in agricultural practices will impact their activities. Nevertheless, adopting AI involves various challenges, such as the lack of robust regulatory frameworks, the investment required to acquire technical tools like sensors, software, and computer hardware, as well as training staff to use them correctly.

Overview of AI Technologies

AI has important applications and developments in smart agriculture, such as crop quality inspection, yield prediction, and pest and disease identification (Chen *et al*., 2023) [2]. However, the use of AI techniques and technologies in agriculture, especially in developing countries, remains low. This is largely because farmers lack the funds, infrastructure, and knowledge required to use advanced AI methods, and the technological systems available to them often do not satisfy the local requirements. In order to overcome these obstacles, modular and adaptable AI-based technologies should be developed and fitted into existing agricultural systems. This survey gives a comprehensive overview of the recent advancements in the AI technologies, applications, and challenges in agriculture. Various AI technologies, such as machine learning, deep learning, and computer vision, are discussed. Applications of AI systems in both crop and livestock industries are explained and categorized into important agri-food tasks. A comprehensive review of the limitations and challenges of implementing AI techniques in agriculture is provided, and potential future research directions are mapped out to further develop the next generation of smart agriculture systems. AI technologies have the potential for agrifood yield prediction through natural images with similar environments. ML techniques, especially the decision tree (DT) approach, are highly relevant for both crop quality assessment and yield prediction. A recent study showed that DL models based on a GoogleNet architecture perform better in fruit grading than conventional ML methods. DL models can automatically learn features from raw data and extract high-level features from images that do not require image preprocessing. AI technologies have demonstrated their potential on different stages of the agri-food chain, such as the inspection of produce quality, pest and disease identification, precision nitrogen fertilization, and livestock monitoring, leading the industry towards intelligence and automation.

Benefits and Challenges

Increasing demand for food is a worldwide challenge exacerbated by slowing production growth rates. Global meat production is expected to continue increasing, fueling demand for feed grains. Crop production is projected to continue increasing. Food systems are the dominant driver for non-greenhouse gas emissions, associated with livestock production. To increase production while reducing costs and negative environmental impacts, Artificial Intelligence (AI) offers some of the best possible approaches. By making highly complicated decisions in a reasonable time, AI has a great potential to optimize agricultural production. Using data from numerous sources to inform and automate decisions at all stages of food systems, AI can help overcome emerging problems such as those related to climate change, labor shortage, and supply chain resilience. In agriculture, AI techniques can be divided into three categories based on the mode of training: supervised learning, unsupervised learning, and reinforcement learning. AI has been applied in agriculture to optimize the use of inputs such as irrigation water, fertilizers, and pesticides; accurately forecast yields, prices, and diseases; model complex systems; and understand genetic architectures (Chen *et al*., 2023) [2].

Despite the great potential of AI technology in agrifood systems, challenges still exist. Five challenges related to agricultural characteristics, external factors, data acquisition and processing, model design and maintenance, and ethical risks are summarized. Agricultural production has unique characteristics such as regionality and seasonality. These characteristics pose new challenges for the application of AI in agriculture. AI models should consider the wide range of agrifood products produced in different regions. The long growth cycle of crops can limit the real-time performance of technologies. Agricultural activities are affected by multiple natural conditions, such as water resources, soil nutrients, terrains, and climates. Climate factors are considered major impact factors on agrifood industries. Developing AI models that are robust across different climates can be challenging. Adverse conditions, such as weak network infrastructure in rural areas of developing countries, can limit the integration of AI and agriculture. Agricultural practices are long and complex processes. Relying solely on a single data resource may not lead to effective judgments and expected outcomes. In the agrifood system, data is often heterogeneous as it is obtained from various sources. Attaining high efficiency in the acquisition, integration, and collaboration of multimodal data has emerged as a major challenge. Designing algorithms with a large amount of data for complex agrifood systems is typically a time-consuming process. The resulting AI models can be sophisticated and have high computational complexity, making deployment difficult for farmers. Maintaining and updating these models is crucial to meet continuous new demands throughout the long growth cycle. In addition to accuracy, efficiency, and practicality, it is important to consider the ethical risks associated with adopting AI models (Aljaloud *et al*., 2022) [1]. AI solutions are frequently employed in critical decision-making scenarios that involve access to private data. Improper use of such data can result in various legal issues. Lack of transparency can undermine the trust of farmers and consumers, leading to their reluctance to adopt AI solutions.

Plant Disease Diagnosis

A crop/plant or farming economics depicts a positive scenario in the agro-economy of the country as there was a commendable growth in the production level of all farm commodities for the last 6-7 years (Aljaloud *et al*., 2022) [1]. It would, of course, look bright in the light of the alleviation of poverty and the attainment of the desired economic growth. Among others, the proper and judicious use of inputs for the production of crops, such as seed, fertilizer, pesticide, irrigation, and other agri-inputs sold by the industries and private entrepreneurs at the village/sub-division/block level, is the most crucial determinant of attaining sustainable agricultural growth.

Besides these achievements, there are many dark aspects that are either grim in nature or need corrective measures for sustaining the agro-economy of the country. The agricultural land is shrinking due to fragmentation every year, while the population growth is increasing. Independently or jointly, these two factors have already started putting tremendous pressure on crop productivity, which has decreased alarmingly. Another major adversity is the erratic and untimely occurrence or distribution of monsoon rain, which vitally affects the entire agricultural calendar. Even the undeniable abundance in food production enthusiasm cannot keep pace with the other adverse factors knocking the world’s food security and food sovereignty (Olubusola *et al*., 2024) [8]. Therefore, the long-term and globally tested remedy for conflict resolution is stability and sustainability, which has become imperative and is now being strived for worldwide. Basically, this is intimately associated with management activities, starting from planning (Evaluation of opportunities and constraints) to implementation through intervention (Delivery of recommendation through technology transfer) and monitoring (Assessment of intervention impact over time). Of these, intervention activities, particularly those related to technology transfer, are most crucial for meeting the sustainability and food security target. One such emerging instrument for transforming today’s agriculture from a conventional to a modern one is the use of artificial intelligence (AI).

Traditional Methods

In developing countries, the methodology of diagnosing plant diseases has been to adopt traditional methods, which are the most basic steps to understand the disease (Singh *et al*., 2022) [14]. In this method, farmers recognize the problem-posted crop from a variety of symptoms. The method describes all the visible features, e.g., spots, wilting, yellowing, discoloration, which are obvious to the farmers. This method of observation is not only naive but also erratic. It was later found that several disturbances give rise to crops. Damage caused to plants due to injury, environmental hazards, nutrient deficiency may resemble symptoms of pest-induced diseases. Thus, an understanding of various diseases, along with their symptoms, is highly essential for diagnosis. Considering this fact, numerous manuals and literature on symptoms of plant pathology were prepared by specialists (Olubusola *et al*., 2024) [8]. Farmers, and agricultural extension workers were trained to utilize the manuals and interpret the symptoms. Another expert knowledge-driven approach was the development of expert systems and decision support systems based on the symptoms. These systems were helpful to farmers in the absence of specialists. However, the approach had its own limitations. The representation of detailed symptoms in textual format, though straightforward, is tedious. Further, after identification of the disease, the search for control measures is difficult in the absence of knowledge about the various control measures relevant to each disease. The control measures follow-up is important, as these measures should be followed for some specific period until there is no possibility of any more chances of reinfestation of the crop.

Role of AI in Disease Diagnosis

Disease Diagnosis Traditional plant disease diagnosis techniques include visual inspection, laboratory-based tests, and expert knowledge-driven systems. Visual inspection is a preliminary technique based on visual symptoms observable on different parts of a plant for disease presence (Olubusola *et al*., 2024) [8]. It is cost-effective, allows early disease detection, and provides real-time decision-making, but it may lack accuracy (Proper identification is only done by an expert), is subject to bias and variability (The same symptoms can be caused by multiple agents), and may limit scalability (Depends on the expertise of professionals). Laboratory-based tests involve growing microbes in favorable conditions to assess various systemic aspects of the plant and using advanced techniques for disease detection such as polymerase chain reaction (PCR) test, bioassays, and chromatography. While providing quantitative data on infection severity/pathogen load/disease progression, they are expensive (Require specialized equipment, reagents, and trained personnel), time-consuming (Up to weeks for some techniques), and require trained personnel with expertise in plant pathology for proper interpretation of results. Expert knowledge-driven systems focus on the identification expertise of specialists to develop an accurate identification system based on expert knowledge and frequently depend on explicit rules or decision trees (Such as IF-THEN rules), making the reasoning behind diagnoses transparent. They can support decisions regarding design, selection, interpretation, prediction, and diagnosis applied to agricultural problems. However, they are limited in scalability (rely on the expertise of specialists), and a high degree of knowledge dynamic accrual is required (the specialists' knowledge may not be up to date).

Role of AI in Disease Diagnosis Despite the drawbacks of the conventional methods, there is a fear and doubt related to new technologies (Particularly AI) that they could take their jobs away (Singh *et al*., 2022) [14]. Meanwhile, there have been continuous efforts to apply new technologies like AI to disease diagnosis decorrelated from the previous fear and doubt. There have been successful implementations that yielded positive results. Machine learning applications include disease detection on a single leaf and multiple diseased leaves, disease identification on fruit, image data augmentation algorithms, disease detection using deep learning, and disease detection without image data. Conclusively, AI has transformed disease diagnosis from traditional methods to innovative and efficient methods.

Methods of Artificial Intelligence in Plant Disease Diagnosis: Artificial intelligence is a wide-ranging field of technology where computers perform tasks that humans consider intellective. Specifically, computers imitate human cognition and thinking processes in various fields, including agriculture, healthcare, economy, telecommunication, etc. One of the main areas of artificial intelligence is machine learning. Through algorithms or sets of rules, it allows systems to find patterns in data automatically and then make inferences about future data based on those patterns. Methods focused on making inferences from the past observations are supervised learning models. Methods analyze hidden patterns about unseen data without any experience or prior rules, which is called unsupervised learning models. Models that are able to learn through both paths are considered hybrids of supervised and unsupervised models (Yao *et al*., 2023) [16]. There are numerous methods of artificial intelligence, but mainly, there are two ways used for crop or plant disease diagnosis: machine learning and deep learning. Utilization of image processing based on machine/deep learning has proven to be crucial in the field of crop disease detection and diagnosis (Singh *et al*., 2022) [14]. In machine learning, pattern recognition methods are the same, but feature extraction is needed before applying the classifier to the detected objects, while in deep learning, feature extraction and classifier are trained jointly. Statistical methods are also used for the detection and segmentation of crop diseased regions.

Machine Learning Algorithms

When examining the advancements and potential of Artificial Intelligence (AI) technology, it appears the most talked about topic of AI is machine learning (ML), which is a sub-field of AI and is earning a lot of interest in different aspects of life. Agriculture is considered one of the core fields for human existence, and it is the most important agricultural sector. There are many ventures of ML for improving the lives of human beings and agriculture was/is the main field for human survival. Agriculture has a long history, and until today, it is performed with many challenges, such as the climate, soil, seeds, land occupation, fertilizers, watering, diseases, and pests, which influence the crop yield. Traditionally, farmers use their experiences to detect different illnesses. However, they need help identifying the disease type, especially in widely grown crops that are similar in external features. With the advancements of ML algorithms in performing different complex tasks in association with computerized cameras or smartphones, many research works of ML-based systems have emerged to tackle these issues in agriculture tools to timely detect losses from different plant diseases (Tilahun *et al*., 2022) [15].

With the growth of several miniature and low-cost spectral cameras, there are emerging opportunities for spectral imaging-based systems for early visualizing and classifying diseases. Several spectral ML models are depicted using different wavelengths in order to demonstrate their usefulness and limitations in the classification of diseases before visual symptoms appear which, in turn, mislead a farmer's management practice. Consequently, it can finally give an overview of the emerging spectral imaging cameras relevant to plant disease diagnosis. Highlighting the power of ML algorithms to formulate crop plant disease diagnostic systems and provide vision-based technologies to improve farmers' bio-safety management practices is one of the main aims of this work. The LM and RIDGE ML algorithms outperform others in all research investigations mentioned.

Approaches of using existing datasets and building a novel dataset that incorporates diseased, healthy, and environmental disrupted plants are proposed to foster plant disease detection research (Yao *et al*., 2023) [16].

Deep Learning Techniques

Machine learning is a technique that allows computers to learn from experience, effectively doing their own programming. In the context of diagnosing plant diseases, machine learning techniques can be utilized to analyze large datasets of images (Yao *et al*., 2023) [16]. A dataset containing images of diseased plants is first created, and the data is pre-processed to improve the quality of the images. The size of the dataset is divided into training and testing datasets, with the training set containing the majority of the data, and the testing set containing a smaller amount. There are various techniques that can be used in the training stage of the learnt model. The training dataset is used to train the machine learning model. During this stage, the palm diseases are classified based on several characteristics such as color, size, shape, texture, etc. The learnt algorithm is then saved, and this saved model can be later used to classify the testing dataset of palm images. The testing dataset is used to test the trained algorithm in which the assigned class of category pest has to be predicted by the learnt model (Singh *et al*., 2022) [14]. There are several machine learning methods that can be used such as Suport Vector Machine, k-Nearest Neighbor, and Naive Bayes.

Applications of AI in Plant Disease Diagnosis

Artificial Intelligence (AI) is applied in agriculture for crop monitoring and early detection of diseases. The large amounts of data collected via the internet of things and remote sensors are systematically analyzed to identify the appropriate solutions (Aljaloud *et al*., 2022) [1]. AI is helping change the traditional agriculture systems and practices to a new, efficient, and effective smart agriculture systems. AI has previously been applied in industries like banking, automobile sales, healthcare, and pharmaceuticals to achieve high accuracy and efficiency in prediction and decision-making. AI in agriculture involves the integration of various techniques such as big data, deep learning, cloud computing, machine learning, and the internet of things to minimize the negative environmental influences and increase the effectivity of the agricultural implementation (Singh *et al*., 2022) [14]. Precision agriculture requires the use of AI and drone technology to assist and enhance precision agriculture activities. Artificial intelligence takes horticulture to the next level by enabling drones to detect diseases in vegetation. These systems can perform scanning, monitoring, and diagnosing with specific cameras installed on drones. Artificial intelligence can also detect crop diseases using images and remote sensors. Drones can compare images collected from an earlier time to identify the affected area and prevent it from spreading. AI works as a system in precision agriculture. Sensors capture data, and this data is transmitted using the internet of things platform, where artificial intelligence algorithms are applied, and the outcome is sent to the user in the simplest manner.

Crop Monitoring and Early Detection

Monitoring crop fields during the growing season can make or break a farmer's economic prospects. Several current monitoring approaches rely on expensive and bulky machinery that can only be deployed preemptively or limit the ability to conduct comprehensive harvest inspections. Keeping in mind the various crop growth stages, the many types of chemicals, including fertilizers and pesticides needed, and the different types of crops that need to be managed, it is impossible to make a completely efficient daily field segment and chemical usage plan. Since early detection of problems in crop fields is so vital, it is no wonder that farmers strive for technologies that provide low-cost but high-accuracy solutions. AI enables detection, descriptions, and predictions based on the similarity of the observable and easily measurable attributes of the crops in the regions of interest relative to the previously labelled parts of the fields (Kulkarni *et al*., 2021) [7]. Here, a farmer can analyze whether to spray a herbicide on a wide area of similar crops. Should weeds appear, the farmer can spray the chemical on the monitored crop part based, again, on a simple classification of the dramatically different attributes of the weed-crop observable traits. A similar but much more complex detectable change in trends arising regarding economic implications would be a farmer's decision to build a second harvesting crew based on the observation that the earlier harvestable areas recover much faster than expected relative to the crop growth model.

As one might imagine, there are many similar possible applications for a technology that estimates the biometric growth parameters of crops, such as calculating the LAI (Leaf area index). These enable a farmer to improve on pesticide and fertilizer efficiency and avoid problems such as spray drift, crop burn, or environmental damages by using fertilizers on crops that do not need them, etc. One direct effect of precision agriculture is a reduction in the amount of chemicals that diminishes farming costs, and notable environmental implications can arise from using AI for this purpose. The AI technologies that are mostly implemented in agriculture are based on neural networks, which are powerful mathematical tools trained to recognize any arbitrary input-output mapping based on examples (Aljaloud *et al*., 2022) [1]. They have been successfully used in various industrial applications for monitoring, describing, reconstructing, and predicting all kinds of deterministic dynamic processes.

Precision Agriculture

Precision agriculture aims to optimize farming practices and improve profitability by understanding the variations in the field. With sensors generating massive amounts of data, AI has the potential to revolutionize precision agriculture (Chen *et al*., 2023) [2]. AI can enhance haze detection with improved accuracy and robustness, making it the preferred solution for monitoring haze density in precision agriculture. The agricultural sector plays a key role in ensuring food security and healthy nutrition for the growing population. The adoption of precision agriculture is crucial in developing countries to increase crop production even in less fertile soils and unfavorable climatic conditions. Emerging AI-based technologies can ensure efficient resource utilization and improved crop management to prevent yield losses due to plant diseases, pests, and nutritional deficiencies (Aljaloud *et al*., 2022) [1].

Limitations and Ethical Considerations

The application of artificial intelligence algorithms in plant disease diagnosis is accompanied by various limitations, which may prevent the effective use of such methods in agricultural production. The first aspect that affects the performance of the AI system is that it requires a large dataset for training, validation, and classification. Many important datasets of plant diseases exist, but most datasets have few examples of specific diseases or some categories are missing. Furthermore, most publicly available datasets contain images acquired in the same conditions, which may make the models ineffective in real agricultural production. Furthermore, data imbalance can be a huge challenge in building a model which considers classifying categories equally. In many datasets, there is a significant unbalance between images of healthy plants and images from sick plants. If the input to the algorithms is not balanced, they tend to learn the majority, which impairs the recognition of certain sick diseases (Barbedo, 2020) [4].

Another aspect that limits the efficient application of AI methods in agriculture is the possible over fitting of the model. Over fitting can occur when using a validation dataset with images acquired in the same conditions as the input data used for training. As a result, the algorithm appears to be good at classifying the images but does not work accurately with the classification of images in different conditions. Therefore, when a CNN is trained with images from some dataset, it should always be evaluated using images acquired in different conditions from those used for training. When specificity is high, the number of false negatives is low, but the number of false positives is high. Thus, generalization is not good at classifying healthy plants, and the model tends to classify most images as sick. On the other hand, when sensitivity is high, the number of false positives is low, but the number of false negatives is high. Hence, generalization is not good at classifying sick plants (Singh *et al*., 2022) [14].

Data Privacy and Security

With the increasing application of Artificial Intelligence (AI) across various domains, the focus has shifted to how AI systems are designed, developed, and used and whether ethical and societal consideration of human safety, fairness, and accountability are incorporated into their lifecycle (Radanliev *et al*., 2024) [10]. There is increasing interest and concern about whether deployed AI systems may adversely impact people, with calls for greater attention to the ethical consequences of AI. Agriculture, constituting the backbone of human society, is amidst AI transformation, and there are pertinent questions about the ethical and security considerations of using AI to detect plant diseases.

The use of AI for diagnosing plant diseases often requires the collection of agricultural data about the farmer and his/her plants (Kotal *et al*., 2023) [6]. This data generally contains sensitive information that needs to be handled with care. Robust data protection is essential to ensure the ethical and secure use of this technology, including protecting such data from data leaks or misuse. This section focuses on the paramount importance of data privacy and security in the context of AI application in agriculture.

Bias and Fairness Issues

The presence of bias and fairness issues in AI systems for image and video plant disease diagnosis is of ethical concern in all real-life applications where the algorithms might harm individuals. Some potentially harmful effects of bias include fallacious image and video recognition, questioning the ownership of identified objects, and providing biased information or advertisement (Risser *et al*., 2022) [11]. If algorithmic discrimination is used in diseased plant diagnosis, farmers or agricultural workers might receive wrong, false, or delayed alerts about diseased plants. In addition, workers might be treated unfairly regarding the suspicion of being responsible for diseased crop outbreaks.

Despite these potential threats, the design and implementation of fair algorithms have not been actively pursued by the agricultural farmer community. The non-existence of fairness metrics in the agricultural data sets also prevents the examination and audit of decision-making transparency (Ferrer *et al*., 2020) [3]. As a future work, it is planning to fill the fair algorithm gap in the agricultural community and raise awareness of the potential dangers of biased algorithms. The general ethics of AI must also be addressed, namely the mitigating measures that need to be in place when deploying such tools in real-life applications.

Future Directions in AI for Plant Disease Diagnosis

This overview peels back the layers of what lies ahead with artificial intelligence (AI) in the diagnosis of plant diseases. Technologies now emerging promise gains in precision and efficiency that were little more than dreams not that long ago, and that could radically rewrite agricultural practice. This view, however, may be overly rosy. Still on the path are daunting technical hurdles. Augmenting that, the institutional setup of the agricultural sector may not be readily conducive to the adoption of AI-enabled systems, which in any case are unlikely to be altogether free of unintended social consequences. Nevertheless, the potential contribution of AI to a more secure and sustainable food supply can ill afford to be ignored (Salman *et al*., 2023) [12]. Achieving that contribution will be a challenge for scientists and engineers, practitioners and managers, as well as policymakers and regulators, to second guess the technology on offer, and consider systems whereby it can evolve to the benefit of us all.

As networked connected devices capable of constant observation proliferate, the availability of data on natural and anthropogenic systems will improve exponentially. Thanks to advances in high-performance computing, our ability to handle large datasets and carry out complex simulations is already rapidly improving. Human sensor contributions, though formidable, will be dwarfed by the data streams generated by a world embedded with devices that sense, communicate and, to a lesser extent, perform computations. Sparking the imagination, there arise visions of an "internet" of physical things, whose properties, states and interactions are continuously monitored, shared, cross-compared, and articulated to people living ontologically and epistemologically elsewhere (Yao *et al*., 2023) [16]. Accountable for all of this is that ever-present drop in the cost of computing that is a necessary condition of the phenomenon dubbed the third industrial revolution, or the better-known information revolution.

Advancements in AI Technologies

Focusing on the advancements in AI technologies, potential future developments in AI for plant disease diagnosis are outlined in this section. Insights into the evolving AI landscape and its implications for agriculture are presented. The transformative impact of future AI advancements in plant disease diagnosis is forecasted. With the rapid advancements in AI technologies, such as natural language processing, generative adversarial networks, and explainable AI, the future of AI systems holds great promise (Olubusola *et al*., 2024) [8]. As models like ChatGPT continue to improve, they could significantly enhance agricultural information dissemination and plant disease diagnosis. AI image processing has made remarkable progress recently, with applications in various fields. The advent of vision transformers represents a new paradigm in AI image processing, and when applied to plant disease diagnosis, state-of-the-art results can be achieved (Singh *et al*., 2022) [14]. It is anticipated that farm-generated images, whether by farm investigators or farmers themselves, could be collected and automatically diagnosed in real-time using generative adversarial networks. With advancements in locally-installed apps generating images for this purpose, easy access to developed AI technologies by farmers is also expected. Additionally, with the advent of explainable AI, prospects for developing explainable AI models for plant disease diagnosis are anticipated. Explanations for AI-generated results can assist model developers in fine-tuning their systems. Furthermore, explanations can aid doctors and farmers in better understanding AI-generated results, thereby increasing their trust and adoption of AI technologies.

Integration with Internet of Things (IoT)

Unlike the previous AI methodologies for plant disease diagnosis that work as standalone solutions, future advancements can pivot towards integrating AI with the Internet of Things (IoT). The general idea behind the Internet of Things (IoT) is to connect a multitude of devices to the internet that can collect, send, and receive data. IoT solutions can prove invaluable to agriculture as IoT devices can aid farmers in continuously monitoring environmental conditions and growing crops more efficiently. However, it generally implies the need for additional post-harvesting processes and systems to handle the collected data. Therefore, this can be a promising direction as different farming parameters could be monitored continuously (Singh *et al*., 2023) [13]. Moreover, through image capturing devices (Such as smartphones), these IoT solutions could also collect frequent crop images, which can act as an additional data source for the early diagnosis of crop diseases. Since AI-driven image-based crop disease classification systems have shown promising results based on publicly available datasets collected from the web, it is expected that with the additional data, these AI models will perform robustly. With these additional systems and the design of a smart agricultural setup, a reliable system for monitoring all the parameters required for better crop yield and early disease detection could be developed. Considering the future advancement of the plant disease diagnosis system through the integration of AI and IoT, it was aimed to realize the potential synergies between AI and IoT in terms of plant disease diagnosis (Jha *et al*., 2023) [5]. The agriculture sector can greatly benefit from enhanced agricultural practices and disease diagnosis from these two emerging technologies. Besides that, discussions were elaborated on the architecture of IoT solutions in agriculture.

Conclusion

Agriculture is experiencing a global transformation due to rapid urbanization and population growth. Moreover, the alarming effects of climate change such as droughts, floods, and soil erosion have compelled the need for a paradigm shift in the agricultural sector. Accurate diagnosis and timely treatment of diseases are crucial for the sustainable growth of any crop. Intelligent systems can play a significant role in the growth of the agricultural sector in developing countries. The development of artificial intelligence techniques has opened the door to innovations. In recent times, artificial intelligence has penetrated the agricultural sectors. The various artificial intelligence tools were analyzed for the detection of phytosanitary diseases in agriculture. This process has been able to represent precise results by using them. Hence, timely diagnosis and treatment of the disease before its huge outbreak is of utmost importance. However, in many developing countries, the absence of a smart agricultural approach hinders accurate disease diagnosis and treatment, impacting large crop production.

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