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ADVANCING CROP HEALTH: THE ROLE OF ARTIFICIAL INTELLIGENCE IN DISEASE MANAGEMENT

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ABSTRACT

Plant pathogens pose significant challenges to global agriculture, threatening crop yields, food security, and economic sustainability. Traditional management strategies often fall short due to the unpredictable nature of diseases and resistance to chemical treatments. The advent of artificial intelligence (AI) offers transformative solutions in this domain. This review explores the integration of AI in detecting, identifying, and managing plant pathogens with unprecedented precision. Key AI methodologies such as machine learning, deep learning, and reinforcement learning are analyzed, highlighting their role in disease diagnosis, pathogen classification, and decision support systems. The potential of precision agriculture, driven by AI tools, to optimize resource use and mitigate environmental impact is also discussed. Despite its promise, AI adoption faces challenges such as inadequate data quality, high computational requirements, and limited trust in automated systems. Emerging technologies and interdisciplinary approaches are paving the way for more effective, scalable, and sustainable plant disease management systems. This review highlights AI's transformative potential in plant pathology, offering insights into its capabilities, limitations, and the innovations required to build a resilient and sustainable agricultural future.

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Plant pathogens, consisting of fungi, bacteria, viruses, or nematodes, are integral components of agricultural and natural ecosystems. Particularly, the wide range of plant pathogens can multiply and spread on plants when landscape, climatic, and cultural conditions are favorable. These pathogens cause significant diseases, impacting crop health from early growth stages to maturity. This pre-harvest damage invariably decreases yield and food security. Consequently, the economic cost of diseases in trade and agribusiness is also staggering (Ristaino et al. 2021; Fones et al. 2020; Rizzo *et al*. 2021; Richard *et al*. 2022; Pandit *et al*. 2022; Ahmed & Yadav, 2023; Mehmood *et al*. 2023).

While eliminating plant pathogens is a goal, practical control strategies are needed to manage these deadly diseases in an efficient and environmentally benign manner. Currently, disease management at the farm relies on the appreciation of pathogen biology, monitoring the environment for potential infection periods, enhancing the capabilities of the crop to resist pathogen attack, and finally developing chemicals that target pathogen biology (Khan *et al*. 2021; Mondejar *et al*. 2021; Nižetić *et al*. 2020; Bradu *et al*. 2022). Traditionally, plant pathologists identify and implement disease management strategies by combining classical and new technologies to monitor, quantify, and predict the progress of targets. However, typically these methods fall short because diseases progress unpredictably, weather and human use of chemicals alter crop quality, and pests develop resistance to chemicals (Rubio *et al*. 2020; Dhanaraju *et al*. 2022). Thus, overly intensive chemicals and cultural management inevitably lead to increased input costs and unwanted side effects on farm sustainability. Therefore, advanced technologies are needed to improve the detection and sustainability of disease management (Danda & Dileep, 2024; Omboni *et al*. 2020; Green *et al*. 2020).

Fundamentals of Artificial Intelligence in Agriculture

Artificial intelligence refers to the general capability of a machine to imitate intelligent human behavior. There are several components that can be utilized to build AI systems, for example, the collection of data, and the development of algorithms, machine learning techniques, and data analytics. AI can be modeled to make decisions like a human and then increase its performance on those tasks by learning over time (Sánchez *et al*. 2020; Gil *et al*. 2021; Yu *et al*. 2022). Within the agricultural world, AI offers diverse benefits, including improved decision-making and resource optimization, such as enhancing the judgment process for element management in agricultural ecosystems as well as growing effective use of resources, in conditions of minimizing expenses and maximizing profit (Lakshmi and Corbett 2023; Rane *et al*. 2024). Other outcomes stemming from the use of AI include a deeper understanding of disease pathology and plant abiotic stress, the diminishment of crop loss, additional environmental benefits, as well as using national resources gained from reduced use of expensive agrochemicals for food security and poverty relief in developing nations. (Han *et al*. 2024; Sparrow *et al*. 2021; Javaid *et al*. 2022; Rejeb *et al*. 2022).

The applications of computer software can be categorized into two classes: functional and strategic. Traditionally, computer usage has been a continuous aid to strategic decision-making. However, AI has provided farmers with an opportunity to automate operational decisions regarding the day-to-day activities required to manage farm resources, e.g., the use of data from yield monitors to control compound fertilizer applications. Historically, an example of AI would be where a set of interacting variables could be used to optimize a decision (Madeira *et al*. 2024; Fuentes-Peñailillo *et al*. 2024; Li & Wang, 2024). As time has moved on, GIS has come to hand, and within the last decade, evolved into precision agriculture, where several outstanding factors yield useful operational management tools for a decision to underpin variable rate applications. In the context of agricultural systems, transformative AI is an innovative study that should provide long-term solutions for controlling diseases that integrate combined technical and practical knowledge for the sustainable management of plant pathogens. As such, the anticipation is that this concept will be scalable and would contribute strongly to the sustainability concepts for plant disease control and integrated pest management (Gul and Banday2024; Brandon & Bommu, 2022; Balaska *et al*. 2023; Abdullah *et al*. 2023 Abo-Elyousr *et al* 2021).

Overview of AI Techniques for Plant Pathogen Detection

Several techniques of artificial intelligence are used to recognize plant pathogens and diseases and are sketched here in detail. Crop yield can be augmented by the timely recognition of disease. In an IPM strategy, early, precise, and quick disease identification is essential to preventing damage. The use of AI in disease recognition offers distinct benefits and applications over earlier research (Orchi *et al*. 2021; Singh *et al*. 2020; Jackulin & Murugavalli, 2022). Artificial intelligence aids in the classification of potentially hazardous samples such as plant pathogens. It facilitates big data via large-scale and automated scientific discovery across the complete data spectrum, from initial identification to subsequent analysis. AI facilitates real-time examination, extending from regular condition observation to understanding situations of urgent and extreme concern. Last but not least, despite being extremely large and spread all over the world, computer, field, and computer-based proxies and extensive understanding can be exploited in singular and common layouts (Aggarwal *et al*. 2022; Li *et al*. 2021)

Several classifications for hyperspectral imaging and its applications are available, and this review emphasizes agriculture. Techniques for pattern detection utilize methods such as neural networks. Convolutional neural networks have been applied to accurately analyze and label plants in open environments. A number of training dataset editions have been employed in this research (Ranjan *et al*. 2024; Al-Khasawneh *et al*. 2023; Zhang *et al*. 2024). Countless examples from the field sustain an overall assessment of 84.4 percent accuracy. The AI use illustrated here is the frequent analysis of lower-level disease signals. In principle, it would be possible to combine meteorological data and plant features with disease and machine learning models to predict preferences and rate monitoring models (Avanzato *et al*. 2023; Baker & Xiang, 2023; Siddiqui *et al*. 2023; Sekar *et al*. 2022)

Machine Learning Algorithms for Disease Identification in Plants

A large quantity of data is produced daily in the arena of science and engineering. Many research areas use algorithms to help in the process of processing and analyzing this data. In terms of plants, they are important for both living beings and the environment. Diseases in plants cause significant financial losses. Identifying and classifying plant diseases is complex and time-intensive. Each plant disease differs in its symptoms. A variety of machine learning algorithms are used to categorize and identify crop diseases. This text is about how to leverage modern and future machine learning algorithms to help control plant pathogens by determining and classifying diseases in plants in order to manage them. (Ahmed & Yadav, 2023; Wani *et al*. 2022; Jackulin & Murugavalli, 2022; Domingues *et al*. 2022; Li *et al*. 2021; Javidan *et al*. 2023). This text explores a wide range of research results related to using machine learning algorithms to categorize and diagnose diseases in plants. Based on the data, the performance of the classifiers might be influenced. Eigenfaces are proposed as a technique. Face detection based on AdaBoost cascade classifier, SURF, HOG, and LBP is discussed. Gaussian Control is one of the techniques utilized in plant disease identification. There are three types of machine learning algorithms: supervised, unsupervised, and reinforcement learning methods. In supervised learning, the data is labeled. The training and validation of the models depend on the entire labeled dataset. SVM, k-means, k-NN, CNN, Naive Bayes, classifier with rules, and other algorithms are included (Kumar *et al*. 2022; Ahmed & Yadav, 2023; Goel & Nagpal, 2023; Javidan *et al*. 2023; Wani *et al*. 2022; Zamani *et al*. 2022). In unsupervised learning, no labeled data is provided to the system. K-means, Gaussian mixture models, hierarchical clustering, and so on are used. Reinforcement learning works similarly to autonomous learning. Machine learning methods have both advantages and drawbacks. The algorithms are beneficial, but they are not without their flaws. In a lesser amount of time, these techniques can detect and classify a large amount of data. In generating improved outcomes, the algorithms must be trained with a large labeled dataset. Increased power consumption, overfitting, multi-image processing, and so on are some of the drawbacks. In machine learning, algorithm selection is critical since it dictates the algorithm's adaptability in various ecosystems. In solving real-world issues, the algorithms are used as the initial step in proof of concept. It produces excellent results. Plant disease management can benefit from machine learning solutions (Liu *et al*. 2022; Ahmad *et al*. 2023; Sujatha *et al*. 2021; Wani *et al*. 2022; Thakur *et al*. 2022; Shoaib *et al*. 2023; Li *et al*. 2021; Balafas *et al*. 2023).

- **Supervised Learning Methods**

Supervised learning plays a crucial role in solving the plant disease identification problem. It processes labeled data to learn from known outcomes and establishes the relationship between the input features and the output labels. The labeled datasets consist of samples with input information and the class labels of these samples. The supervised learning model can generalize the knowledge from these labeled data and predict the output labels for new samples (Li *et al*. 2021; Jackulin & Murugavalli, 2022; Sujatha *et al*. 2021). Several powerful machine learning techniques have been developed that work on supervised learning, for instance, the decision tree, support vector machines, the k-nearest neighbor algorithm, and the artificial neural network. All these techniques aim to extract and model the relationship between the input features and the output labels of the data samples. The decision tree models analytical relationships, while support vector machine models logical relationships. The k-nearest neighbor algorithm computes data similarity, and the neural network models both analytical and logical relationships. (Shoaib *et al*. 2023; Wani *et al*. 2022; Ahmad *et al*. 2023; Albattah *et al*. 2022)

The supervised learning model built from the input features and output labels can classify diseases and, in regression models, it also predicts the occurrence of disease with a continuous value when the input values match any value from the training dataset. However, labeling data can be challenging since mislabeled samples can lead to poor model performance. Thus, the training dataset quality has a strong effect on the model when making predictions for new samples. Many successful application examples have been reported for supervised learning in predicting plant diseases (Ahmed & Yadav, 2023; Kumar *et al*. 2020; Domingues *et al*. 2022; Liu *et al*. 2022). Such examples provide intuitive evidence of the important role of machine learning for applications in crop health management systems. Supervised learning can provide accurate predictions of disease identification and predict the occurrence of disease (Elbasi *et al*. 2023; Domingues *et al*. 2022; Ahmed & Yadav, 2023; Kundu *et al*. 2022; Ahmad *et al*. 2023)

- **Unsupervised Learning Methods**

Unsupervised learning methods are widely used for clustering, anomaly detection, dimensionality reduction, and association rule learning. These methods can be used to discover hidden patterns and relationships among the variables of interest in the data. Unlike supervised learning methods, unsupervised methods do not need labeled data; that is, they examine only the input data without corresponding output variables. In the case of plant disease image recognition, unsupervised methods can be used to recognize new diseases or new symptoms of existing diseases in crops by analyzing the data, just as human experts do. Unsupervised learning techniques include clustering, principal component analysis, independent component analysis, and t-distributed stochastic neighbor embedding. (Yan & Wang, 2022; Domingues *et al*. 2022; Shahi *et al*. 2023; Wani *et al*. 2022; Jafar *et al*. 2024) These techniques are applied in various studies related to plant disease identification, although the two most common techniques are clustering and dimensionality reduction (Benfenati *et al*. 2023; Benfenati *et al*. 2021).

Unsupervised learning methods are more flexible and useful for real-world pathogen identification because they address several challenging problems and can handle large, high-dimensional datasets, making them more suitable for agricultural sensor data. However, successful applications of such unsupervised learning methods require feature selection and data preprocessing prior to their application in order to reduce the dimensionality of the data and remove unimportant details and noise. The overview summarized here demonstrates the general capabilities of supervised and unsupervised learning techniques along with traditional classification techniq (Goodswen *et al*. 2021; Rahman *et al*. 2024; Castellanos *et al*. 2024; Srivastava *et al*. 2024; Tang *et al*. 2024; Mamdouh *et al*. 2023; Sandholtz *et al*. 2023)ues.

- **Reinforcement Learning**

Distinct from the models we have introduced before, reinforcement learning is a type of machine learning that enables agents to recognize incentive mechanisms that guide their behaviors in seeking long-term rewards in complex, non-stationary, and multi-agent setups by trial and error. In a typical RL setup, there exists an agent that interacts with its environment to learn a series of strategies or policies to opt for actions that maximize, or otherwise meet particular requirements, accumulative rewards, or utilities. The principles and even the math behind RL also involve explicitly the ideas of maximizing long-term rewards (Gautron *et al*. 2022; Jackulin & Murugavalli, 2022; Rane *et al*. 2024). Accordingly, it is considered to be the third of the three basic learning types. One side of the contemporary application of RL in agriculture focuses on various strategies for plant disease management where the environment with which the agent interacts is dynamic, uncertain, and non-stationary, and continuous learning from the feedback of the environment is hence crucial (Attri *et al*. 2024; Wani *et al*. 2022; Shaikh *et al*. 2022; Attri *et al*. 2023; Akintuyi2024; García-Vera *et al*. 2024).

So far, some relevant methods or strategies could be mentioned, such as Q-learning, Sarsa, DQL, and policy gradient, etc. Among those, Q-learning is one of the first successful models in RL, which has been theoretically proven to converge to the optimal policy under the Markov Decision Process. However, DQL, a variant of Q-learning, shows a significantly impressive adaptive learning ability for complex large-scale systems. Using deep learning as a DQL makes it possible to work in extensive state spaces (Li *et al*. 2024; Sun *et al*. 2023; Faisal *et al*. 2024). Unlike traditional Q-learning, DQL has the ability to approximate the action-value function by a deep neural network, which represents the Q-table in the form of a deep learning model. This methodology shows significant promise in the field of plant disease control due to the capability of predicting phenotypes at an early stage (Ji *et al*. 2024; Canay & Kocabıçak, 2024). However, the application and adoption of reinforcement learning models in the field of agriculture continue to pose significant challenges. Unfortunately, the majority of the attempts that have been made thus far have been highly constrained in terms of their suitability for use in agricultural environments. Necessarily, the continuous feedback provided by the environment necessitated the construction of an environment, an action, and the cause that had the ability to respond to the action. An agriculturally oriented action could be anything that can be quantified. The design of such a reinforcement environment is far from simple (Minn, 2022; Abbasi *et al*. 2024)

Deep Learning Applications in Plant Pathogen Control

Deep learning algorithms have the ability to automatically make decisions or learn to make decisions through a set of rules known as learning processes. They are designed in the form of networks, and in fact, they do a great job in image-based fields. The most commonly used deep learning models in disease detection are the CNNs. Convolutional neural networks are made up of various layers, including the convolutional layer, the pooling layer, the dropout layer (which is used to drop out a number of neurons randomly during the learning process), and the fully connected layer, which is used to carry out the learning process (Reshi *et al*. 2021; Sharma *et al*. 2020). The nodes of CNNs are locally connected. This nature of CNNs is very important in observing and detecting images, so it is widely used to classify the diseases and detect them from the images. Deep learning algorithms are far superior to common and traditional machine learning algorithms because of their ability to handle big data and manage large images (Thakur *et al*. 2023; Tugrul *et al*. 2022; Khattak *et al*. 2021).

Deep learning algorithms have the ability to manage and train the data sets in an intelligent way and improve the accuracy of the results obtained. Since deep learning is considered to be the modern form of artificial intelligence, it has a good impact on the improvement of an industry (Tchito *et al*. 2021; Panigrahi *et al*. 2020; Ibrahim and Abdulazeez 2021). In the field of plant disease detection and classification, some research and studies apply many different deep learning algorithms in the farms and in the fields, such as deep feed forward networks, LeNet models, AlexNet modules, Inception models, deep learning model based on the SqueezeNet model, ensemble of deep learning, and aggregation based on residual networks. These applications show that the deep learning networks and algorithms can be applied in classifying images or detecting diseases in the fields (Panchal *et al*. 2023; Goyal and Singh2023; Shetty *et al*. 2022; Wani *et al*. 2022; Rana & Bhushan, 2023)

AI-Driven Precision Agriculture for Disease Management

Precision agriculture in the AI era is working rigorously to generate and analyze relevant data that may influence important decisions for the particular agro-ecosystem. Collecting, storing, and analyzing data with the application of AI technologies may generate predictive models for optimizing management practices. Precision agriculture utilizes the integration of information based on technology (Bhatti *et al*. 2024; SS *et al*. 2024; Monteiro *et al*. 2021). The main aim of precision agriculture is to make more rational decisions for improving farm management by controlling many factors to optimize crop yields. Precision agriculture can be refined for plant pathogen and disease management in the form of AI in smart and molecular farming, leading towards precision agriculture. The enhanced approach can be helpful as sustainable and effective (Singh *et al*. 2021; Murugan and Kaliyanandi2024; Coulibaly *et al*. 2022; Madeira *et al*. 2024)

The application of AI in precision agriculture, integrated with an ecosystem component driving towards AI, can be used in creating a model for every ecosystem as a whole. AI is successfully used in crop disease management with the help of:

- Unmanned Aerial Vehicles,
- optimization algorithms with sensor descriptions,
- convolutional neural image detection,
- advanced machine learning classification,
- the Iris method of disease detection, and (
- spatiotemporal image analysis to monitor crop health.

These approaches with different integrated circuits help us to understand that both diseases can be described procedurally by their development based on the environment and are complementary (Li & Wang, 2024; Sharma & Shivandu, 2024). AI can be used for early precision agriculture where real-time disease is sensed with the help of IoT sensors. AI-driven precision agriculture shows early sensing of pathogens by sensors and then autonomous action of UAVs for spraying directly on the infected patch, resulting in enhancement of yield and cost support. It has been found that AI tools help accurately assess the development of crown rot and fusarium head blight to facilitate more efficient fungicide applications that will adequately protect yield and quality. With the use of an integrated approach, the system would facilitate precision agriculture, and along with the control of the disease, we could foresee an eventual optimization of resources. Implementing precision agriculture is yet challenging due to the capability of technology (Gul and Banday 2024; Javaid *et al*. 2023). Recently, practices have been described with advancements, and technology highlights the probable chances to control plant health. In spite of the facts and advancements, challenges exist such as the cost of hardware, software, IoT device sensors, connectivity, and the presence of data islands or silos, linking them for applications that require domain-specific knowledge (Orchi *et al*. 2021; Abdullah *et al*. 2023). Overall, combining sustainability, fresh products, and human health, a proper management protocol is needed to bring more innovative solutions. It is concluded that with the advancement in technology, AI-driven precision agriculture for plant health is a new and complementary area where all agricultural sectors need smart, sustainable, and regenerative solutions for existing yields to cover global food needs (Mahlein *et al*. 2024; Corceiro *et al*. 2023; Shaikh *et al*. 2022).

Challenges and Limitations of AI in Plant Pathogen Control

The successful application of AI in the domain of plant-pathogen interactions is constrained by several challenges, including the need for high data quality. The training dataset used should reflect the field conditions, include diverse host-pathogen interactions, and be of sufficient size. Plant-pathogen interactions are complex and influenced by multiple factors, including weather conditions. Consequently, the dynamic nature of the pathosystem may lead to limited accuracy of the AI prediction models; in some cases, a lack of generalization across environments may be observed. The demand for appropriate computational resources may limit access to the technology, as well as the need for bioinformatics and AI expertise (Jeger *et al*. 2024; González-Rodríguez *et al*. 2024). Issues of compliance, data sharing, ethical and social implications, and local needs must be considered when implementing AI tools for the control of plant pathogens. AI technologies for plant pathogen control are promising, yet a cautious interpretation of their performance and application is necessary. There are further interdisciplinary topics that need to be discussed in order to evaluate the need for AI in the intensively monitored domain of plant pathology. Due to unfamiliarity with a novel AI application, trust might need to be built over time through validation by researchers, industries, and growers. It is important to consider the ethical dimensions of AI applications in plant pathology and agriculture; for example, privacy should be considered when linking genotype data with phenotype data and plant protection recommendations (Santos-Briones *et al*. 2024). Giving advice using AI could also raise questions concerning the responsibility and accountability of all entities in the decision-making process. Even if these systems are capable of making complex analytical decisions automatically and agricultural experts are guiding the underlying algorithms, the technology is not widely adopted as there is a lack of widespread trust in AI to address the requirements stipulated above. Many of the challenges were raised and anticipated by the informants of this study. For example, the need for large, diverse, field-relevant datasets and the requirement for computational capacity are barriers for small businesses. Disciplinary meetings are needed to improve understanding of the potential benefits of AI technologies (Crandall *et al*. 2020; Jeger *et al*. 2021; González-Rodríguez *et al*. 2024).

Future Directions and Emerging Technologies

Emerging AI technologies, such as deep learning integrated with IoT sensors, will enable rapid and cost-effective pathogen diagnostics to guide proactive disease management Pathogen Identification: Could learning where pathogens are in a field be a way to use AI in managing crop diseases? There are emerging technologies in machine learning, data analytics, and sensors that can further reduce the cost of agricultural monitoring with advanced pathogen and pest interventions. Besides the already discussed categories, emerging technologies in bioinformatics such as precision genomics and ecological metagenomics can provide a way of understanding pathosystems in the environment to guide intervention (Qazi *et al*. 2022; Javaid *et al*. 2023). With the advances in agriculture, the integration of big data exploitation with emergent technologies in AI can result in a significant advancement in plant pathology concerning environmental interactions and sustainable intensification. The current research over various global architectures, preprocessing techniques of the data, the evolution, and adaptation of pathogen interventions with rapidly evolving pathogens and predictions from the model are subjects of further research to make AI intervention dependable. The integration of AI and the Internet of Things is another exciting area that is currently being considered for precision agriculture to combine other relevant data outside plant health status and the interconnectedness of processes and practices between growers and end-users, as today's agricultural systems are increasingly adopting digital agriculture tools (Singh *et al*. 2021; Mohamed *et al* 2022; Akintuyi 2024). AI operates and is subject to changes in inputs and external factors, and there needs to be continued research and progress in bioinformatics and agriculture to design and use AI interventions that can adapt quickly to the ever-changing environment. AI in agriculture will only grow in relevance, as agriculture is increasingly threatened by climate change with changes in crop diseases and the potential to impact global food security. AI has a role to play through gene discovery and big data analyses, especially concerning precision genomics and ecological genomics. There is potential for integration with AI, especially in terms of developing decision support systems that can guide intervention at the plant–microbe–biotic interface (Fuentes-Peñailillo *et al*. 2024; Gupta *et al*. 2020).

This review highlights AI's transformative potential in plant pathology, offering insights into its capabilities, limitations, and the innovations required to build a resilient and sustainable agricultural future.

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