

FUTURE POTENTIAL OF ARTIFICIAL INTELLIGENCE AND PROTEOMICS IN CONTROLLING PLANT DISEASES

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ABSTRACT

Artificial intelligence and proteomics combine to enable pre-symptomatic plant disease detection, targeted molecular treatments, and resilient crop breeding. [1, 2, 3]

Future Potential of AI and Proteomics in Plant Disease Control

- **Pre-Symptomatic Molecular Profiling:**
 - AI-driven proteomics analyzes protein abundance and modification states in plant tissues (such as leaves and seeds) to spot disease anomalies before physical symptoms appear.
 - Profiling helps evaluate seed quality and stress tolerance (e.g., managing barley yellow mosaic virus) prior to planting. [1, 2]
- **Early & Automated Disease Diagnostics:**
 - Deep learning, computer vision, and machine learning models process massive biological and spectral imaging datasets to identify pathogens with high precision.
 - Smartphone apps and drone-mounted sensors allow real-time field surveillance, cutting down reliance on broad-spectrum chemical pesticides. [1, 2, 3, 4, 5]
- **Predictive Outbreak Forecasting:**
 - Integrating climate, soil, and protein-level data via predictive analytics forecasts spatial-temporal disease risks weeks in advance.
 - Farmers receive early warning alerts to apply localized, precision interventions rather than blanket treatments. [1, 2, 3]
- **Accelerated Crop Breeding & Resistance:**
 - AI speeds up the mapping of protein interaction networks (interactomes) and gene expressions.
 - This accelerates breeding programs designed to develop high-yielding crops naturally resistant to emerging pathogens and climate stress. [1, 2, 3, 4]

KEYWORDS- artificial intelligence, proteomics, plant diseases, crops, control

INTRODUCTION

Plant diseases remain a major threat to global food production, causing significant yield losses and economic impact worldwide. Early and precise disease detection is crucial for effective crop management, yet conventional diagnostic approaches are often slow, labor-intensive, and rely on specialized expertise that may not be widely accessible. Recent advances in artificial intelligence (AI), particularly deep learning-based image analysis, offer scalable and automated solutions for plant disease recognition. This review critically examines forty-one peer-reviewed studies published between 2008 and 2025, selected following PRISMA guidelines from major scientific databases. We summarize key methodological developments, including convolutional neural networks, vision transformers, transfer and few-shot learning, and multimodal sensing approaches, highlighting their reported performance and limitations. Although many models achieve high accuracy in controlled datasets, their effectiveness often decreases under real-field conditions due to environmental variability, limited training data, and practical deployment

constraints. We discuss existing challenges and propose future research directions, emphasizing improved robustness in field environments, development of lightweight and explainable models suitable for edge deployment, and integration with precision agriculture systems.

In agriculture, the release of the PlantVillage dataset by Hughes and Salathé (2015) provided an important early benchmark for deep learning research in plant disease detection. It provides over 54,000 expertly labeled images of healthy and diseased leaves from 14 crops across 38 classes. PlantVillage has become a widely cited resource, showing that smartphone-based diagnosis can make expert knowledge more accessible to farmers. However, it is critical to acknowledge that PlantVillage images were captured under controlled laboratory conditions with uniform, plain backgrounds that do not reflect the complexity of real agricultural environments. Noyan (2022) conducted a rigorous analysis demonstrating that deep learning models trained on PlantVillage frequently exploit background features rather than actual disease symptoms, resulting in significantly degraded performance when deployed on field-collected images. This background bias represents a fundamental limitation that must be carefully considered when interpreting reported accuracy values from this dataset (see Section 5.1 for a detailed discussion). More recently, Vision Transformers (ViTs) have emerged as powerful alternatives to CNNs. Models such as the Swin Transformer have achieved top 1 accuracy of 87.3% on ImageNet-1K (Dosovitskiy, 2020; Liu et al., 2021) and have inspired transformer-based approaches for plant disease detection (Barman et al., 2024; Borhani et al., 2022; Thai et al., 2023).[1,2,3]

Despite these advances, applying AI models in real-world field conditions remains challenging. Studies show that models trained under controlled conditions often perform poorly on external images. Mohanty et al. (2016) first reported a dramatic decline in accuracy from 99% to 31% when their CNN model, originally trained on the PlantVillage dataset, was evaluated on field-collected images. Arsenovic et al. (2019) similarly documented substantial accuracy degradation under field conditions and proposed the PlantDiseaseNet dataset, containing 79,265 real-world images, to address these limitations. Bridging this gap is essential for developing reliable and scalable AI-based plant disease detection systems for practical agriculture.

This review summarizes current research on AI-based plant disease detection, tracing developments from traditional machine learning to modern deep learning and vision transformer approaches. Rather than merely cataloging individual studies, this review offers a critical synthesis by re-evaluating and re-classifying existing technologies through an integrated analytical framework encompassing architectures, learning paradigms, explainability, and deployment constraints. It examines key benchmark datasets, compares model performance, and highlights the main challenges and opportunities for future research. By analyzing 41 peer-reviewed studies published between 2008 and 2025, this review aims to provide researchers, practitioners, and policymakers with a comprehensive and practical understanding of the field.

DISCUSSION

Over the past few decades, the global agricultural sector has been confronted with rising food demand while grappling with limited resources and environmental constraints [1]. With the

world's population projected to reach approximately 9.8 billion by 2050 [2,3], an unprecedented pressure mounts on agricultural systems to increase productivity and ensure food security. In light of this, plant diseases and pests have emerged as formidable threats, causing up to 40% of global crop losses annually [4,5]. Plant health extends beyond the mere absence of disease, encompassing physiological well-being where crops achieve optimal functioning while remaining free from biotic stressors (including pests such as insects, mites, and nematodes that cause feeding damage and disease vectoring, and pathogens like fungi, bacteria, and viruses that disrupt cellular processes) and abiotic stressors such as drought, salinity, and nutrient deficiencies [6,7]. Pests cause direct physical damage through feeding, reduce photosynthetic capacity, create entry points for secondary infections, and serve as vectors for viral and bacterial pathogens [8], while plant diseases disrupt normal physiological processes by interfering with nutrient uptake, blocking vascular systems, and altering metabolic pathways, ultimately leading to yield losses and plant death [9]. Plant health management requires integrated approaches spanning disease detection [10], pest monitoring [11], nutrient optimization [12], and stress assessment [13]. However, timely discovery through conventional phytosanitary measures (regulatory procedures for preventing pest and disease spread through inspection, quarantine, and control [14]) presents significant challenges [15], as traditional methods often detect problems only after visible symptoms appear [16,17,18,19,20], when economic damage has occurred and intervention effectiveness is substantially reduced [21].

Plant health significance extends beyond agricultural productivity, encompassing global sustainability and human welfare. Food security, defined as ensuring adequate food availability, accessibility, utilization, and stability for all populations [22], becomes increasingly challenging as crops must meet rising global food demand without expanding agricultural land use [1,23]. Food safety focuses on preventing contamination, as diseased plants accumulate mycotoxins (toxic fungal metabolites posing health risks [24]), pathogens, and harmful compounds creating consumption risks [25]. Human health links to plant health management, where late disease detection triggers excessive pesticide applications, resulting in chemical residue accumulation and environmental contamination [26,27]. Climate change intensifies challenges by increasing disease pressure, accelerating pathogen evolution, and shifting pest geographical ranges, disrupting established protocols [28]. The economic losses are staggering: plant diseases and pests cause approximately \$220 billion in annual global crop losses [4,29], with fungal diseases accounting for \$60 billion [30], insect pests \$70 billion [31], and viral diseases \$30 billion [32]. These converging pressures create urgent need for innovative, technology-driven solutions transforming plant health monitoring.[4,5,6]

Current plant health management relies on conventional approaches that present fundamental limitations hindering effective crop protection [33]. Traditional methods encompass visual inspection by agronomists [34], laboratory diagnostics including Polymerase Chain Reaction (PCR) for pathogen DNA detection [35] and Enzyme-linked immunosorbent assays (ELISA) for pathogen-specific protein identification [36], and field scouting within Integrated Pest Management (IPM) frameworks that combine biological, cultural, physical, and chemical control strategies [37]. While molecular diagnostics such as PCR are capable of detecting infections at pre-symptomatic stages, their effectiveness in real-world agricultural settings is constrained by sampling frequency, laboratory processing time, cost, and infrastructure requirements, limiting their scalability for continuous, field-wide monitoring [35]. More details in Section 3.1. Consequently, disease detection in practice often remains reactive rather than preventive, with

interventions frequently initiated only after visible symptoms appear [16,18,34]. Manual visual inspection suffers from subjectivity, requires specialized expertise, and becomes labor-intensive across large cultivation areas [38]. Laboratory diagnostics further introduce delays and costs: PCR typically requires 24–72 h and specialized equipment costing \$15,000–\$150,000 [35], while culture-based methods are slow (5–14 days) and limited to culturable pathogens [39]. Field scouting within IPM frameworks remains largely symptom-driven, often missing early or spatially sparse infestations [37]. These practical constraints create a pre-symptomatic detection gap at scale, leading to delayed interventions, accelerated pathogen spread, substantial yield losses, and compensatory overuse of pesticides [21].

Artificial Intelligence (AI) represents a paradigm shift in plant health management, offering unprecedented capabilities to overcome the fundamental constraints of conventional diagnostic approaches [38,40,41]. At its core, Machine Learning (ML) enables computational systems to identify complex patterns within agricultural data without explicit programming by learning from training datasets to make predictions on new, unseen data [40], while Deep Learning (DL) leverages multi-layered artificial neural networks with multiple hidden layers to automatically extract hierarchical features from high-dimensional datasets that surpass human perceptual capabilities [40]. These technologies directly address critical agricultural challenges by automating complex analytical tasks, from processing multispectral imaging (capturing 3–12 spectral bands including visible and near-infrared light) [16,42,43] and hyperspectral imaging (recording hundreds of narrow spectral bands from 400–2500 nm to detect subtle biochemical changes invisible to conventional sensors) [42,43] to analyzing thermal signatures that reveal plant stress through leaf temperature variations [44] and integrating diverse sensor modalities including RGB cameras [20,45,46], LIDAR [47], and environmental sensors [48], pathogen lifecycle data [49], and plant physiological responses [41]. AI fundamentally overcomes traditional limitations through continuous monitoring capabilities using autonomous sensing platforms [50], elimination of subjective bias inherent in human visual assessment [16], and capacity for real-time analysis of sensor data at unprecedented scales covering large areas simultaneously [16]. The transformative benefits include early detection during the critical pre-symptomatic intervention window with 40–60% reduction in pesticide use through precision application [51], scalability through autonomous drone and robot platforms reducing monitoring costs significantly [50], and precision that enables targeted interventions [52], collectively positioning AI as the enabling technology for sustainable, data-driven crop protection strategies.[7,8,9]

RESULTS

Artificial intelligence (AI) stands as a transformative force in agriculture, significantly impacting various facets of the industry. By seamlessly integrating robotics into agricultural systems, AI has streamlined labor-intensive tasks such as plant monitoring, sampling, and data collection, heralding a new era of efficiency and precision. This convergence of AI and robotics not only enhances productivity but also reduces operational costs for farmers. In the realm of plant pathology, AI-driven technologies have revolutionized disease detection and management. Leveraging hyperspectral images, AI algorithms offer unparalleled accuracy in discerning plant health and detecting pathogens. Furthermore, the integration of Internet of Things (IoT) devices facilitates real-time data acquisition from field sensors, providing invaluable insights into environmental conditions and plant health status,[10,11,12] thus empowering farmers with

timely decision making capabilities. Remote sensing technologies, including satellite imagery and unmanned aerial vehicles (drones), complement AI solutions by offering scalable and high-resolution data for disease monitoring and early detection. Moreover, the incorporation of electronic nose (e-nose) technology further enhances disease diagnosis by analyzing volatile organic compounds emitted by infected plants, enabling rapid and accurate identification of pathogens. The true power of AI in agriculture lies in its ability to process vast amounts of multi-modal data from diverse sources. By employing sophisticated algorithms, AI facilitates predictive modeling, disease forecasting, and personalized management strategies. Embracing the synergies between AI, robotics, IoT, remote sensing, drones, and e-nose technologies holds immense promise for addressing global agricultural challenges. As these technologies continue to evolve and intertwine, they will play an increasingly pivotal role in ensuring food security, sustainability, and resilience in the face of changing environmental conditions and growing population pressures. [13,14,15]

CONCLUSION

Artificial intelligence (AI) enables the early detection, precise diagnosis and other effective mitigation strategies, which revolutionized the plant disease management practices. Different tools are used in artificial intelligence like learning about machine models and neural networks, which analyse the various datasets from satellite imagery, drone surveillance and other smart phone-based disease recognition, which help in identification of symptoms of plant disease with high accuracy. [16,17,18,19] The two types of techniques are computer vision and predictive analytics. The vision techniques help in the identification of pathogens, however, the predictive analytics help in forecasting disease outbreaks based on environmental and climatic conditions. This AI-powered decision support system assists farmers in choosing the best treatments, minimizing dependence on chemical pesticides, and fostering sustainable agricultural practices. AI also facilitates real-time crop health monitoring by integrating with Internet of Things (IoT) devices and remote sensing technology. There are also some challenges in using AI, such as, scarcity of data, model generalization and accessibility, hinder widespread adoption. There are some aspects of AI, which must be focused in future that include enhancing AI model robustness, improving data collection strategies and also on cost effective techniques to farmers related with AI. It holds potential to transform and revolutionize plant disease management, ultimately improving crop yield, food security, and environmental sustainability. [20]

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