E-ISSN: 2789-3073
P-ISSN: 2789-3065
Impact Factor (RJIF): 5.78
www.plantpathologyjournal.com
IJPPM 2025; 5(2): 60-66
Received: 22-05-2025
Accepted: 25-06-2025

Deepa Srivastava
Assistant Professor, Plant Pathology Laboratory, Department of Botany, Deen Dayal Upadhyaya Gorakhpur University, Gorakhpur, Uttar Pradesh, India

Correspondence
Deepa Srivastava
Assistant Professor, Plant Pathology Laboratory, Department of Botany, Deen Dayal Upadhyaya Gorakhpur University, Gorakhpur, Uttar Pradesh, India

AI-powered innovations in plant pathogen detection: Transforming agriculture through technology

Deepa Srivastava

DOI: https://www.doi.org/10.22271/27893065.2025.v5.i2a.145

Abstract
The integration of artificial intelligence (AI) into plant pathogen detection is transforming agricultural practices by enabling more efficient, accurate, and scalable disease management solutions. Traditional diagnostic methods, while effective, often require significant time, expertise and laboratory resources, limiting their application in large-scale and real-time scenarios. AI-powered innovations, including machine learning (ML), deep learning (DL) and computer vision, are revolutionizing the detection and diagnosis of plant diseases. These technologies analyze vast datasets from sources such as high-resolution imaging, genomic sequences, environmental sensors, and remote sensing platforms to identify pathogens with unprecedented precision. AI-driven tools, such as mobile-based diagnostic apps, autonomous drones, and predictive modeling systems, empower farmers and agricultural stakeholders with real-time insights into disease outbreaks and progression. Additionally, AI enhances the interpretation of metagenomic data, facilitating the identification of novel and unculturable pathogens. This paper explores the transformative potential of AI in plant pathogen detection, highlighting its contributions to sustainable agriculture, early disease management, and food security. It also addresses challenges such as data availability, model reliability, and ethical considerations, paving the way for future advancements in AI-driven plant pathology.

Keywords: AI, plant pathogen detection, machine learning, deep learning, smart agriculture, precision farming, biosensors, computer vision, early warning systems

Introduction

Plant health is crucial for global food security as it ensures the production of sustainable and profitable crops, protects biodiversity, and mitigates the spread of pests, which are exacerbated by global trade and climate change, threatening agricultural sustainability. With increasing threats from pests, diseases, and climate change, maintaining plant health is essential for sustainable agricultural practices. Healthy plants are foundational for high crop productivity, with estimates indicating that 30-40% of potential yields are lost annually due to plant health issues. Diseases such as wheat stem rust and Coffee Wilt Disease exemplify the severe impact of plant health on food availability [1]. Global yield losses can amount to hundreds of billions of dollars, exacerbating poverty and food insecurity, particularly in developing nations. Plant health is linked to food safety, as unhealthy plants can harbor pathogens that affect both human and animal health [2].

Traditional pathogen detection methods in plants face significant challenges that hinder effective disease management. These methods are often time-consuming, labor-intensive, and require extensive taxonomical knowledge, making them less suitable for rapid diagnostics in agricultural settings. The requirement for extensive culturing and morphological analysis adds to the time burden, especially for biotrophic pathogens that are difficult to culture [3].

These methods necessitate skilled personnel for accurate identification, which can be a barrier in resource-limited settings. The complexity of sample handling and the need for specialized equipment further complicate the diagnostic process. Traditional techniques often lack the sensitivity and specificity required to detect low pathogen loads, leading to false negatives [4]. The inability to differentiate between closely related pathogen strains can result in misdiagnosis, complicating management strategies. Despite these challenges, there is a growing trend towards integrating advanced molecular and portable diagnostic technologies that promise to enhance the speed and accuracy of pathogen detection.

The integration of Artificial Intelligence (AI) in agriculture is increasingly recognized as a transformative force, addressing the urgent need for rapid, accurate, and scalable solutions in food production. AI technologies enhance decision-making, optimize resource management, and improve crop yields, thereby revolutionizing traditional farming practices. Machine learning algorithms can predict crop yields and market demands, helping farmers optimize planting schedules and resource allocation. Precision agriculture, facilitated by AI, allows for targeted interventions that improve crop resilience against diseases and pests [5].

Overview of Plant Pathogens and Detection Challenges

Plant pathogens pose significant challenges to agriculture, leading to substantial economic losses and food security issues. The detection of these pathogens is critical for effective management and control, yet it is fraught with difficulties.

Detection Challenges

Low Titer and Uneven Distribution: Many pathogens exist in low concentrations within plants, making them difficult to detect. Their uneven distribution further complicates sampling and diagnosis.

Latent Infections: Some pathogens can remain dormant, leading to delayed detection and potential outbreaks.

Inhibition Issues: Nucleic acid extraction processes often face inhibition problems, reducing the sensitivity of molecular detection methods [6].

Advancements in Diagnostic Tools

Molecular Techniques: The use of PCR and RT-PCR has increased, providing rapid and accurate detection methods. Real-time PCR, in particular, has shown high throughput capabilities [7].

Field-Deployable Devices: There is growing interest in point-of-care devices that allow for on-site testing, enhancing the speed and efficiency of pathogen detection.

Integrated Protocols: Combining molecular techniques with other biological methods can improve diagnostic accuracy and reliability. Despite these advancements, challenges remain, particularly in developing universally applicable detection methods and addressing the complexities of pathogen biology [6].

Limitations of conventional diagnostic tools (Microscopy, ELISA, PCR): Plant diseases significantly impact agricultural productivity and economic stability, necessitating effective diagnostic tools for management. Conventional diagnostic methods, including microscopy, ELISA, and PCR, face several limitations that hinder their effectiveness in real-world applications. These challenges include issues of sensitivity, specificity and scalability, which can delay timely interventions and exacerbate economic losses. Microscopy requires skilled personnel for accurate identification, which can be labor-intensive and time-consuming. Often lacks sensitivity, making it difficult to detect low levels of pathogens[7]. ELISA (Enzyme-Linked Immunosorbent Assay) while faster than traditional methods, it can produce false negatives and requires specific antibodies, which may not be available for all pathogens[8]. High costs associated with reagents and equipment limit its widespread use. PCR (Polymerase Chain Reaction) although highly sensitive, PCR is expensive and labor-intensive, making it impractical for large-scale field applications. Despite these limitations, the integration of advanced technologies such as next-generation sequencing and optical sensing offers promising alternatives for more efficient and accurate plant disease diagnostics.

Artificial Intelligence in Agriculture: A Paradigm Shift

The integration of Artificial Intelligence (AI) in agriculture represents a significant paradigm shift, enhancing traditional farming practices through advanced technologies such as machine learning (ML), deep learning (DL), computer vision (CV) and natural language processing (NLP). These components collectively enable smart farming, which optimizes resource management and improves productivity [9].

Role of AI in Smart Farming

AI analyzes vast datasets from IoT sensors, drones, and satellites to provide actionable insights on crop health and resource allocation. AI-driven systems enhance efficiency in water usage, fertilizer application, and pest management, leading to reduced waste and environmental impact [9].

Advantages of AI-Powered Pathogen Detection

Speed: Rapid identification of pathogens allows for timely interventions, minimizing crop loss.

Scalability: AI systems can be deployed across large agricultural areas, ensuring consistent monitoring and management.

Accuracy: Advanced algorithms improve detection rates, reducing false positives and negatives in pathogen identification.

Automation: AI automates labor-intensive tasks, freeing up resources for more strategic activities [5].

AI-Powered Techniques for Pathogen Detection

Supervised and unsupervised learning techniques play a crucial role in the classification of plant diseases, with algorithms like SVM, Random Forest, and Decision Trees being widely used for this purpose. These methods are essential for developing automated systems that can detect and classify plant diseases early, thereby enhancing crop yield and promoting sustainable agriculture. The integration of machine learning and deep learning techniques has shown promising results in improving the accuracy and efficiency of disease detection systems.

Support Vector Machine (SVM): SVM is frequently used for plant disease classification due to its high accuracy. For instance, SVM with RBF kernel achieved a 98.48% accuracy in classifying brinjal leaf diseases [10]. It also outperformed other classifiers in stem disease detection with an 87% accuracy [11].

Random Forest: This algorithm is valued for its robustness and ability to handle large datasets. It was used effectively in plant leaf disease detection, achieving a 79% accuracy in stem disease classification [11].

Decision Trees: Known for their simplicity and interpretability, Decision Trees are used in conjunction with other models like CNN for feature extraction and classification [12]. Unsupervised learning can be used for clustering and anomaly detection in plant disease datasets. This approach can help in identifying new or rare diseases by grouping similar patterns without prior labels.

CNNs for image-based disease detection
Convolutional Neural Networks (CNNs) have emerged as a powerful tool for image-based plant disease detection, offering significant improvements over traditional methods. These models control deep learning techniques to accurately classify and diagnose plant diseases from image data, which is crucial for enhancing agricultural productivity and ensuring food security. Customized CNN architectures have been developed to enhance feature extraction efficiency, incorporating depth wise separable convolutions, dilated convolutions, and attention mechanisms, achieving high accuracy with reduced computational demands [13].
Datasets such as Plant Village and others from platforms like Kaggle are commonly used, containing images of both healthy and diseased plant leaves [14]. Preprocessing steps include resizing images to a standard size and applying augmentation techniques to improve model robustness. CNN models have demonstrated high accuracy in plant disease detection, with some models achieving up to 99.80% mean average precision (mAP) [13]. These CNN models can be deployed in real-time systems to assist farmers in early disease detection, thereby reducing crop losses and improving agricultural productivity. The models ability to generalize effectively to unseen data makes them suitable for practical applications in diverse agricultural settings. While CNNs offer substantial benefits for plant disease detection, challenges remain, particularly in handling complex backgrounds and variations in disease appearance. Transfer learning and fine-tuning with pre-trained models like VGG-16 and ResNet-50 have been explored to address these issues, showing promising results in improving model accuracy and robustness [14].

RNNs/LSTMs for time-series data and forecasting
Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have emerged as powerful tools for time-series forecasting, including the prediction of plant diseases. Their ability to capture long-term dependencies and complex temporal relationships makes them particularly suitable for agricultural applications, where environmental factors significantly influence disease outbreaks.

Long-Term Dependency Handling: LSTMs effectively manage long-term dependencies, crucial for understanding the delayed effects of environmental factors on plant diseases.

Complex Pattern Recognition: LSTMs can capture both short-term fluctuations and long-term trends, making them adept at modeling the intricate dynamics of disease spread influenced by various factors [15].

Computer Vision Applications
Leaf image analysis for symptom recognition
Leaf image analysis plays a crucial role in the early detection and classification of plant diseases through symptom recognition. Utilizing computer vision techniques, researchers can automate the identification of disease symptoms in leaf images, significantly enhancing the efficiency of agricultural practices [16]. Deep learning, particularly through convolutional neural networks (CNNs), has shown remarkable success in recognizing patterns indicative of disease, outperforming traditional methods like support vector machines (SVM) in accuracy and processing time. Furthermore, effective image segmentation is essential for isolating regions of interest within leaf images, allowing for precise analysis of symptoms [17]. By combining these advanced methodologies, image classification can accurately categorize leaves as healthy or diseased, facilitating timely interventions in crop management. This integrated approach emphasizes the potential of modern technology in transforming agricultural disease management.

Drone/satellite-based remote sensing for large-scale monitoring: Drone and satellite-based remote sensing technologies have emerged as pivotal tools for large-scale monitoring of plant diseases, significantly enhancing agricultural productivity and food security. These technologies facilitate early detection and efficient management of plant pathogens, which are crucial for minimizing yield losses [18].

Advantages of Drone Technology
High Spatial Resolution: Drones equipped with various sensors can capture detailed images, allowing for precise identification of disease symptoms at early stages [18].

Cost-Effectiveness: Compared to traditional methods, drone-based monitoring reduces labor costs and provides real-time data, enabling timely interventions [19].

Automated Data Processing: Advanced image processing techniques, including machine learning algorithms, enhance the accuracy of disease detection by analyzing features extracted from images [20].

Integration with Satellite Technology
Large-Scale Monitoring: Satellite remote sensing complements drone technology by providing extensive coverage, enabling the monitoring of vast agricultural areas for disease outbreaks [5].

Real-Time Data: The combination of satellite and drone data allows for continuous monitoring, facilitating proactive management strategies and timely responses to emerging threats [5].

Smart sensors for real-time data collection
Smart sensors are connected through IoT networks, facilitating continuous data transmission to cloud-based platforms for real-time analytics. The integration of machine learning enables the comparison of real-time data with predefined disease profiles, enhancing the accuracy of disease detection [21]. Early detection systems alert farmers to potential infections, allowing for targeted responses such as precision spraying, which minimizes pesticide use[21]. By reducing reliance on harmful chemicals and optimizing resource utilization, smart sensors contribute to more sustainable agricultural practices.

Effectiveness and Applications

High Accuracy in Disease Detection: Lightweight deep learning models such as Google Net, MobileNetV2 and quantized CNNs have achieved high accuracy (up to 98.25%) in detecting various plant diseases, including those affecting tomatoes and coffee plants, when deployed on edge devices [22].

Real-Time Diagnostics: Edge devices like NVIDIA Jetson, Raspberry Pi, and STM32 microcontrollers enable rapid image classification, with inference times as low as 3.5 ms, supporting timely disease management in the field [23].

Integration with IoT: Combining AI with IoT sensors and smart devices allows for continuous monitoring, early detection, and integration into broader disease management systems (Table -1)

Mobile apps for farmer-assisted disease diagnosis

Mobile apps such as Plantix and Nuru are increasingly used to assist farmers in diagnosing plant diseases, utilizing artificial intelligence (AI) and image recognition. These tools aim to improve early detection, reduce crop losses, and support food security, especially in regions with limited access to agricultural experts.

Plantix: Demonstrated high accuracy (90-100%) in diagnosing major pests and diseases in staple crops like maize, okra, cassava, and plantain in Nigeria. However, its effectiveness is limited for crops not included in its database, highlighting the need for broader crop coverage [24].

Nuru: Achieved 65% accuracy in diagnosing cassava diseases, outperforming both extension agents (40-58%) and farmers (18-31%). Accuracy increased to 74-88% when multiple leaves per plant were assessed. Nuru also slightly improved users' diagnostic skills with practical use [25].

Other Apps: Newer AI-based apps, such as mPD-App, have reported up to 93.9% accuracy in classifying 14 plant diseases, indicating strong potential for reliable diagnosis[26]. Field-tested citizen science tools have shown detection confidence up to 87% for specific pests [26].

Smart greenhouses with automated monitoring

Smart greenhouses with automated monitoring are transforming agriculture by integrating advanced technologies to optimize plant growth, resource use, and sustainability. These systems use sensors, IoT, artificial intelligence, and automation to monitor and control environmental conditions, reducing labor and improving crop yields.

Key Technologies and System Components

Sensors and IoT Infrastructure: Smart greenhouses rely on a network of sensors to monitor temperature, humidity, soil moisture, light intensity, and CO_2 levels in real time data is transmitted via wireless technologies, often using cloud or edge computing for processing and storage [27].

Automation and Control: Automated systems regulate irrigation, lighting, ventilation, and heating based on sensor data. Control units (e.g., Arduino, ANFIS, or other microcontrollers) adjust environmental parameters to maintain optimal plant conditions without human intervention.

Mobile and Remote Access: Many systems offer mobile app interfaces (e.g., Blynk IoT app) for real-time monitoring and remote control, allowing farmers to manage greenhouses from anywhere [28].

Advanced Features and Security

Integration of AI and Deep Learning: Advanced algorithms, such as adaptive neuro-fuzzy inference systems (ANFIS) and deep learning, enhance prediction accuracy and system adaptability [32].

Security Measures: Systems address data security concerns by detecting and mitigating potential IoT network attacks, ensuring data integrity and traceability.

Renewable Energy Integration: Some systems use solar or wind power for operations, further reducing environmental impact.

Robotics and drones in pathogen surveillance

Robotics and drones are transforming plant pathogen surveillance by enabling rapid, large-scale, and precise monitoring of crop health (Table 2). Traditional detection methods are often slow, labor-intensive, and ineffective at early disease stages, while drone-based systems offer high-resolution automated, and cost-effective solutions for early detection and management of plant diseases. Drones equipped with advanced sensors and cameras can identify plant diseases in their early stages. Drones provide detailed, high-resolution data over large areas quickly, making them suitable for both small and large-scale farms [19]. Automated image collection and processing reduce manual labor and increase productivity, enabling frequent and scalable monitoring. Drone-based surveillance lowers the costs associated with manual scouting and excessive pesticide use by targeting only affected areas. Drones are most commonly used to detect blight and fungal pathogens, with crops like grapes, watermelon, and rice being frequent targets [29]. Drones support targeted pesticide application, reducing chemical use and environmental impact. Combining drones with AI and deep learning enhances detection accuracy and supports decision-making for disease management [30].

Data Challenges and Ethical Considerations

Artificial intelligence (AI) is transforming plant disease management by enabling faster, more accurate detection and monitoring. However, the effectiveness and trustworthiness of these systems depend on overcoming significant data challenges and addressing key ethical considerations. Many available datasets are small, laboratory-based or lack diversity, making it difficult to train robust AI models that generalize well to real-world conditions. There is a need for larger, more diverse and well-annotated datasets that cover multiple crops, diseases, and environmental conditions [31]. Integrating and comparing large, multi-dimensional datasets from various sources is complex. There is no standard for model performance assessment, and data from different domains (e.g., lab vs. field) can differ significantly, complicating model development and validation. AI models often struggle with unseen diseases, new environments or different data distributions, limiting their reliability in diverse agricultural settings. Deploying AI in resource-limited environments (e.g. on small devices or in remote areas) requires models with fewer parameters and efficient data processing [33].

Ethical Considerations

AI models can inherit biases from unrepresentative or imbalanced datasets, leading to unfair or inaccurate disease predictions for certain crops, regions or farming communities. Many AI models, especially deep learning systems are "black boxes," making it difficult for users to understand or trust their decisions. Improving model interpretability is essential for responsible deployment. The use of farm and environmental data raises concerns about data ownership, consent, and the potential misuse of sensitive information. Clear accountability is needed for errors or unintended consequences from AI-driven decisions. Ensuring robust, reliable performance in real-world conditions is critical [34].

Future Directions and Research Opportunities

Machine learning models such as random forests, can classify plant samples as healthy or diseased using metagenomics sequencing data without needing prior knowledge of the pathogen's genome. This approach enables detection of both known and emerging diseases, and models trained on one host-pathogen system can generalize to others, supporting broad surveillance efforts. Advanced AI techniques like few-shot learning and lightweight meta-ensembles allow accurate disease detection with minimal data and computational resources. These methods are suitable for real-time, field-based applications and can be deployed on resource-constrained devices, making them practical for digital farming and IoT environments. Combining AI with Internet of Things (IoT) platforms, such as smart sensors and drones, can enable real-time, field-based disease detection and monitoring, improving early intervention and resource management. Emerging techniques like generative AI, Few Shot Learning (FSL), Generative Adversarial Networks (GANs), and Self-Supervised Learning (SSL) can enhance disease identification, prediction, and management, especially in data-scarce environments [35] (Table-3). AI-driven forecasting models that utilizes large, high-quality datasets including climate and sensor data can predict outbreaks and support proactive disease management, especially under changing climate conditions. AI can power global surveillance systems, automate risk analyses, and provide customized decision support for stakeholders, from farmers to policymakers [36].

Developing AI models that perform reliably across diverse crops, diseases and real-world conditions remains a challenge. Research is needed to improve model robustness, generalization, and adaptability to new environments. There is a need for larger, more diverse and publicly available datasets, including in-field images and multi-modal data, to train and validate AI models effectively. Creating open-source, interpretable AI models will build trust and facilitate adoption among farmers and agricultural stakeholders. Most research focuses on detection, future work should expand to prevention, control, monitoring, and especially recovery prediction for affected plants. Making AI tools affordable, user-friendly and accessible to farmers, including those in resource-limited settings, is a critical area for development.

Tables

Table 1: Key Applications and Outcomes

Application Area	AI Technique(s) Used	Real-World Impact/Outcome	Reference(s)
Tomato, Chilli, Potato, Cucumber	ML/DL, IoT, Drones	Rapid, accurate field-based disease detection	[23]
Vegetables & Fruits	DL, Explainable	AI >90% accuracy interpretable predictions	[14]
Potato Disease Management SVM	RF, CNN, MobileNet	64.3-100% accuracy, targeted agrochemical use	[18]
Data-Scarce Scenarios	Few-Shot Learning, ViT	>90% accuracy with minimal data, real-time detection	[35]
Greenhouse/Urban	Farming Robotics, ML, Vision	Automated disease detection, precision agriculture	[27]

Table 2: Technologies and Methods Used

Technology/Method	Description/Use Case	References
RGB & Color-Infrared (CIR)	Imaging Captures plant health indicators and disease symptoms	[29]
Deep Learning (CNNs)	Classifies and diagnoses diseases from drone images	[29, 30]
Edge Detection & Histogram	Equalization Feature extraction from leaf images	[19]
GPS Integration Maps	disease locations for targeted intervention	[27]
IoT and Communication	Protocols Coordinates drone fleets for efficient coverage	[30]

Table 3: Emerging Research Areas and Needs

Area	Research Need/Opportunity	References
IoT	Integration Real-time field-based detection and monitoring	[23, 35]
Advanced AI Techniques	Generative AI, FSL, GANs, SSL for improved diagnosis	[30]
Data & Model	Robustness Diverse datasets, generalizable models	[31]
Comprehensive Management Beyond detection	Prevention, control, recovery prediction	[36]
Interpretability & Usability	Open-source, transparent, accessible tools	[31]

Conclusion

AI is set to revolutionize plant disease management, but future research must focus on robust, interpretable models, integration with IoT, comprehensive management strategies and making solutions accessible to all farmers. Collaboration, data sharing, and innovative AI techniques will be key to overcoming current challenges and maximizing the benefits of AI in agriculture. While the

benefits of AI in agriculture are substantial, challenges such as data privacy, ethical considerations, and the need for technological infrastructure remain critical issues that must be addressed to fully realize AI's potential in transforming agricultural practices.
The successful deployment of AI in plant disease detection relies on close collaboration between computer scientists, agronomists, plant pathologists, and agricultural economists. Addressing challenges such as data quality, model generalization, real-time processing, and socioeconomic barriers requires a holistic, interdisciplinary approach. Looking forward, AI-powered plant pathogen detection is poised to be the backbone of precision agriculture, driving resilience against climate change, population growth, and evolving disease threats. Continued innovation and interdisciplinary collaboration will enable the development of interpretable, scalable, and accessible AI systems, empowering farmers worldwide and securing sustainable food production for future generations.

Acknowledgements
The author is grateful to Head, Department of Botany, Deen Dayal Upadhyaya Gorakhpur University, Gorakhpur, U.P., India, for providing academic support and access to research facilities.

References
1. Food J. The importance of plant health to food security. Food Security. 2010;2(3):215-231. https://doi.org/10.1007/S12571-010-0072-5
2. Manzoor S, Mir ZA, Wani TA, Gulzar H, Nabi Z, Parveen S, Rather TR, Nabi SU. Recent advances in diagnostic approaches for plant pathogen detection. 2024. p. 17-41. https://doi.org/10.58532/v3bfbt3p1ch2
3. Kumar P, Akhtar J, Kandan A, Kumar S, Batra R, Dubey S. Advance Detection Techniques of Phytopathogenic Fungi: Current Trends and Future Perspectives. 2016. p. 265-298. https://doi.org/10.1007/978-3-319-27312-9_12
4. Prasanna N, Choudhary S, Kumar S, Choudhary M, Meena PKP, Saloni S, Ghanghas R. Advances in Plant Disease Diagnostics and Surveillance- A review. Plant cell biotechnology and molecular biology. 2024;25(11-12):137-150. https://doi.org/10.56557/pcbmb/2024/v25i11-128918
5. Gupta A, Vaidya A, Sapra A. Smart Plant Monitoring System and Chatbot. International Journal for Multidisciplinary Research. 2025;7(1). https://doi.org/10.36948/ijfmr.2025.v07i01.35328
6. Verma N, Shukla M, Kulkarni R, Srivastava K, Claudic B, Savara J, *et al.* Emerging Extraction and Diagnostic Tools for Detection of Plant Pathogens: Recent Trends, Challenges, and Future Scope. ACS Agricultural Science & Technology. 2022;2(5):858-881. https://doi.org/10.1021/acsagscitech.2c00150
7. Sharma P, Sharma SK. Paradigm Shift in Plant Disease Diagnostics: A Journey from Conventional Diagnostics to Nano-diagnostics. 2016. p. 237-264. https://doi.org/10.1007/978-3-319-27312-9_11
8. Verma N, Shukla M, Kulkarni R, Srivastava K, Claudic B, Savara J, *et al.* Emerging Extraction and Diagnostic Tools for Detection of Plant Pathogens: Recent Trends, Challenges, and Future Scope. ACS Agricultural Science & Technology. 2022;2(5):858-881. https://doi.org/10.1021/acsagscitech.2c00150
9. Priyadarshini B, Subhadarshini S, Pattnayak A, Nayak S. Artificial intelligence in agriculture. 2024. p. 59-71. https://doi.org/10.58532/v3bcag24ch6
10. Sathya R, Senthilvadivu S, Ananthi S, Bharathi VC, Revathy G. Vision Based Plant Leaf Disease Detection and Recognition Model Using Machine Learning
11. Techniques. 2023. p. 458-464. https://doi.org/10.1109/iceca58529.2023.10395620
12. Akbar MJU, Kamarulzaman SF, Tusher EH. Plant Stem Disease Detection Using Machine Learning Approaches. 2023. p. 1-8. https://doi.org/10.1109/icccnt56998.2023.10307074
13. Varshney D, Babukhanwala B, Khan J, Saxena D, Singh A. Plant Disease Detection Using Machine Learning Techniques. 2022. p. 1-5. https://doi.org/10.1109/incet54531.2022.9824653
14. Sharma S, Vardhan M. Enhanced Plant Disease Detection Using a Custom CNN with Advanced Feature Extraction Techniques. 2024. p. 1-7. https://doi.org/10.1109/icccnt61001.2024.10725398
15. Lawrence MO, Ogedebe P. Detection of Image-based Plant Leaf Diseases Using Convolutional Neural Networks. 2024. p. 1-6. https://doi.org/10.1109/seb4sdg60871.2024.10630105
16. Sushanth T, Siddarda TS, Sathvika A, Shruthi ASS, Lekha A, Kumar TS. Time Series Forecasting using RNN. Indian Scientific Journal of Research In Engineering And Management. 2024;8(11):1-8. https://doi.org/10.55041/ijsrem39164
17. Prasad PY, Ramu M, Reshma S, Priya RC, Anusha P, Reddy BL. Leaf Lens: An Intelligent Vision for Plant Disease Diagnosis using Deep Learning. 2024. p. 1-5. https://doi.org/10.1109/aimla59606.2024.10531537
18. Chand N, Satpathi A, Gehlot T, Tripathi A. Potential of artificial intelligence to combat challenges in transforming agriculture. 2024. p. 192-201. https://doi.org/10.58532/v3bcag6p1ch16
19. Lajurkar MR, Barve AN, Waghmare SJ, Karande R, Kharbade SB, Bagde A, Sathe SK. Applications of Drone for Crop Disease Detection and Monitoring: A Review. Asian Research Journal of Agriculture. 2025;18(1):15-25. https://doi.org/10.9734/arja/2025/v18i1638
20. Abbas A, Alami M, Alrefaei AF, Abbas Q, Naqvi SAH, Rao MJ, *et al.* Drones in Plant Disease Assessment, Efficient Monitoring, and Detection: A Way Forward to Smart Agriculture. Agronomy. 2023;13(6):1524. https://doi.org/10.3390/agronomy13061524
21. Prasanna N, Choudhary S, Kumar S, Choudhary M, Meena PKP, Saloni S, Ghanghas R. Advances in Plant Disease Diagnostics and Surveillance- A review. Plant cell biotechnology and molecular biology. 2024;25(11-12):137-150. https://doi.org/10.56557/pcbmb/2024/v25i11-128918
22. Gupta N. Multidimensional and Revolutionary Relevance of AI in Agriculture. Advances in Environmental Engineering and Green Technologies Book Series. 2025. p. 145-174. https://doi.org/10.4018/979-8-3693-7483-2.ch006

23. Majeed Y, Ojo M, Zahid A. Standalone edge AI-based solution for Tomato diseases detection. Smart Agricultural Technology. 2024. https://doi.org/10.1016/j.atech.2024.100547
24. Jafar A, Bibi N, Naqvi R, Sadeghi-Niaraki A, Jeong D. Revolutionizing agriculture with artificial intelligence: plant disease detection methods, applications, and their limitations. Frontiers in Plant Science. 2024;15. https://doi.org/10.3389/fpls.2024.1356260
25. Akinyemi A, Fadele E, Ojeleye A. Exploring a mobile application for pest and disease symptomatic diagnosis in food crops in Nigeria: Implications of its use by smallholder farmers in sub-Saharan Africa. Ife Journal of Science. 2023. https://doi.org/10.4314/ijs.v25i1.1
26. Mrisho L, Mbilinyi N, Ndalahwa M, Ramcharan A, Kehs A, McCloskey P, *et al.* Accuracy of a Smartphone-Based Object Detection Model, PlantVillage Nuru, in Identifying the Foliar Symptoms of the Viral Diseases of Cassava-CMD and CBSD. Frontiers in Plant Science. 2020;11. https://doi.org/10.3389/fpls.2020.590889
27. Christakakis P, Papadopoulou G, Mikos G, Kalogiannidis N, Ioannidis D, Tzovaras D, Pechlivani E. Smartphone-Based Citizen Science Tool for Plant Disease and Insect Pest Detection Using Artificial Intelligence. Technologies. 2024. https://doi.org/10.3390/technologies12070101
28. Kanagala S, Khalaifin M, Al-Harthi A, Al-Ahdhami S. Greenhouse Farm Monitoring is Automated with Smart Controls. International Academic Journal of Science and Engineering. 2023. https://doi.org/10.9756/iajse/v10i1/iajse1005
29. Shanto S, Rahman M, Oasik J, Hossain H. Smart Greenhouse Monitoring System Using Blynk IoT App. Journal of Engineering Research and Reports. 2023. https://doi.org/10.9734/jerr/2023/v25i2883
30. Chin R, Catal C, Kassahun A. Plant disease detection using drones in precision agriculture. Precision Agriculture. 2023;24:1663-1682. https://doi.org/10.1007/s11119-023-10014-y
31. Refaai M, Dattu V, Gireesh N, Dixit E, Sandeep C, Christopher D. Application of IoT-Based Drones in Precision Agriculture for Pest Control. Advances in Materials Science and Engineering. 2022. https://doi.org/10.1155/2022/1160258
32. Prabin Kumar Sahoo, Deoraj Sharma. Economic impact of artificial intelligence in the field of agriculture. Int J Hortic Food Sci 2023;5(1):29-34. DOI: 10.33545/26631067.2023.v5.i1a.152
33. Shafik W, Tufail A, Namoun A, De Silva L, Apong R. A Systematic Literature Review on Plant Disease Detection: Motivations, Classification Techniques, Datasets, Challenges, and Future Trends. IEEE Access. 2023;11:59174-59203. https://doi.org/10.1109/ACCESS.2023.3284760
34. Lee S, Liaw Z, Chai Y, Ng S, Bonnet P, Goëau H, Joly A. Revolutionizing Plant Pathogen Conservation: The Past, Present, and Future of AI in Preserving Natural Ecosystems. Biodiversity Information Science and Standards. 2024. https://doi.org/10.3897/biss.8.133055
35. Dara R, Fard S, Kaur J. Recommendations for ethical and responsible use of artificial intelligence in digital agriculture. Frontiers in Artificial Intelligence. 2022;5. https://doi.org/10.3389/frai.2022.884192
36. Rezaei M, Diepeveen D, Laga H, Jones M, Sohel F. Plant disease recognition in a low data scenario using few-shot learning. Comput. Electron. Agric. 2024;219:108812. https://doi.org/10.1016/j.compag.2024.108812
37. Garrett K, Bebber D, Etherton B, Gold K, Sulá A, Selvaraj M. Climate Change Effects on Pathogen Emergence: Artificial Intelligence to Translate Big Data for Mitigation. Annual review of phytopathology. 2022. https://doi.org/10.1146/annurev-phyto-021021-042636