JOURNAL OF PLANT RESEARCH AND INNOVATIONS
Jul-Dec 2024, VOL. 2, ISSUE 2, pp. 5-9
https://doi.org/10.61577/jpri.2024.100007

RESEAPRO JOURNALS

MINI REVIEW

OPEN ACCESS

Artificial intelligence in plant disease detection and crop management

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ABSTRACT

Plant diseases remain a major threat to global agricultural productivity, with biotic stressors causing annual crop yield losses of 20–40%, thereby increasing food insecurity amid rapid population growth. Conventional disease management approaches, which rely on visual field scouting and expert diagnosis, are limited by subjectivity, delays, and poor scalability, making them inadequate for modern large-scale agriculture.

In recent decades, artificial intelligence (AI), including machine learning (ML), deep learning (DL), and computer vision, has emerged as a transformative approach in plant pathology and precision agriculture. These technologies provide automated, scalable, and high-throughput solutions for disease detection, severity assessment, and decision support. This review explores key deep learning architectures such as convolutional neural networks (CNNs), transfer learning models (ResNet, EfficientNet, VGG), object detection frameworks (YOLO, Faster R-CNN), and vision transformers (ViT). Their applications span image-based leaf diagnosis, hyperspectral and multispectral imaging, and UAV-assisted field monitoring.

Reported results show disease classification accuracies exceeding 95% under controlled conditions, while detection models achieve mean average precision (mAP) above 90% in real-field environments. Beyond detection, AI is also applied in yield prediction, smart irrigation, integrated pest management (IPM), and soil health monitoring.

However, challenges persist, including limited generalization across environments, insufficient data for underrepresented crops, the black-box nature of DL models, and barriers to adoption in low-resource settings. Future directions include explainable AI (XAI), edge computing, multi-modal data integration, and federated learning, highlighting the need for interdisciplinary collaboration among plant scientists, data experts, agronomists, and policymakers.

KEY WORDS

Plant disease detection; Artificial intelligence; Deep learning; Computer vision; Precision agriculture; Integrated pest management

ARTICLE HISTORY

Received 16 July 2024; Revised 13 August 2024; Accepted 20 August 2024

Introduction

Global agricultural productivity is increasingly threatened by plant diseases that reduce crop yield and quality. The Food and Agriculture Organization (FAO) estimates that plant pests and diseases cause annual crop losses of up to 40%, which results in an economic impact which exceeds USD 220 billion worldwide (FAO, 2021). Crop-specific analyses shows substantial yield reductions in major staple crops which includes wheat (21.5%), rice (30.3%), maize (22.6%), potato (17.2%), and soybean (21.4%), caused by diverse pathogens and pests. These challenges are further increased by climate change, global trade, and evolving pathogen diversity, which enable geographical redistribution and new disease outbreaks [1].

Food security concerns continue to increase as the global population is projected to reach nearly 9.8 billion by 2050, requiring a 50–60% increase in agricultural production. Biotic stresses significantly drive productivity, particularly in developing regions where smallholder farmers experience yield losses exceeding 40% in cereal and pulse crops. Changing climatic conditions change temperature and moisture patterns, creating favourable environments for pathogen proliferation and disease transmission across major agricultural systems. Early and accurate plant disease detection has become a priority for sustainable agricultural productivity and global food security.

Traditional plant disease identification primarily depends on visual inspection of disease symptoms and expert knowledge of plant pathologists. Such methods are often subjective, time-consuming, and influenced by observer variability, leading to inconsistencies in disease diagnosis [2]. Visual disease scoring is particularly challenging when multiple pathogens produce similar symptoms, such as leaf spots, blights, and mosaic patterns.

Delayed disease identification frequently results in excessive pesticide application, increased production costs, environmental contamination, and reduced crop productivity. Limited accessibility to plant pathology experts and extension services further worsen the problem, particularly in resource-constrained agricultural systems.

Artificial intelligence (AI), including machine learning (ML), deep learning (DL), and computer vision, has emerged as a promising solution for automated plant disease detection and precision crop management. AI-based systems can analyse large volumes of image and sensor data to identify disease symptoms with high accuracy and consistency. Convolutional neural networks (CNNs) trained on large datasets such as PlantVillage have demonstrated disease classification accuracy exceeding 99% under controlled conditions, highlighting the potential of AI in plant pathology.

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Advanced deep learning architectures including ResNet, EfficientNet, and object detection models such as YOLO have improved detection performance in complex field environments. Recent developments in vision transformer (ViT) architectures enable improved feature extraction through self-attention mechanisms, enhancing model generalization capability in real-world agricultural scenarios [3]. Addition of AI with hyperspectral imaging, unmanned aerial vehicles (UAVs), and Internet of Things (IoT) sensors have increased disease monitoring from laboratory settings to large-scale agricultural fields.

Models trained on controlled datasets often shows reduced accuracy (70–85%) under field conditions due to variations in lighting, background noise, and disease severity levels. Heavy reliance on datasets such as PlantVillage limits model generalization capability across agroecological environments [4].

Existing review articles primarily focus on image-based disease classification, with limited attention given to the integration of AI in broader crop management practices such as irrigation optimization, pest prediction, and soil health monitoring. Emerging technologies such as vision transformers, multimodal learning, and explainable AI remain insufficiently synthesized within a unified analytical framework.

This mini review aims to critically synthesize recent advancements in artificial intelligence (AI)-driven approaches for plant disease detection and precision crop management [5]. The review focuses on evaluating the performance and applicability of major deep learning architectures, including convolutional neural networks (CNNs), transfer learning models, object detection frameworks, and vision transformer (ViT) models, across diverse imaging platforms such as RGB imaging, hyperspectral sensing, and UAV-assisted monitoring systems.

AI Techniques Used in Plant Pathology

Machine learning vs deep learning approaches

Primary uses of Artificial Intelligence in plant pathology mostly depend on traditional ML algorithms, wherein feature extraction constitutes a critical step. Techniques such as Support Vector Machines (SVM), Random Forests (RF), and K-Nearest Neighbour (KNN) have been largely employed for disease classification using features derived from leaf images, including color histograms, texture descriptors (e.g., Gray-Level Co-occurrence Matrix), and morphological characteristics [6,7]. These approaches demonstrate the classification performance under controlled conditions as their need on domain-specific feature engineering and limited scalability constrained their applicability in heterogeneous field environments.

Deep learning (DL) methods, particularly Convolutional Neural Networks (CNNs), have revolutionized plant disease diagnostics by enabling automated hierarchical features to learn directly from raw image data. Architectures such as AlexNet, VGGNet, ResNet, and EfficientNet have shown superior performance in large-scale image classification tasks. Deep CNN models trained on the PlantVillage dataset achieved classification accuracies exceeding 99%, highlighting the potential of DL in plant disease detection. Transfer learning strategies, involving fine-tuning of pre-trained models on domain-specific datasets, have further improved model generalization.

Object detection frameworks

Beyond image-level classification, object detection frameworks have achieved prominence for identifying disease symptoms within plant tissues. Models such as YOLO (You Only Look Once), Faster R-CNN, and Single Shot Detector (SSD) allow real-time detection and segmentation of infected regions, assisting precise disease quantification and severity assessment. These models are particularly beneficial in field conditions, where multiple disease instances and complex backgrounds are present [8]. Recent studies have reported high detection accuracy and computational efficiency of YOLO-based models for in-field crop disease monitoring.

Emerging approaches

Current advancements in AI have introduced transformer-based architectures, such as Vision Transformers (ViT), which leverage self-attention mechanisms to capture long-range dependencies in images. Hybrid CNN-transformer models have also been suggested to combine the spatial feature extraction capability of CNNs with the global contextual understanding of transformers [9]. Also, self-supervised learning approaches are gaining traction, enabling models to learn strong feature representations from unlabeled datasets and eminent consideration in agricultural domains where labeled data are scarce.

Collectively, these AI techniques have pointedly advanced the precision and scalability of plant disease detection systems, although challenges related to model interpretability and real-world operation remain areas of active research [10].

AI in Plant Disease Detection

Artificial Intelligence (AI)-assisted plant disease detection has emerged as a highly efficient approach for improving diagnostic precision, assisting early intervention, and minimizing crop losses [11]. Current improvements in computer vision and deep learning have assisted automated identification of disease symptoms using diverse imaging modalities under both controlled and field conditions.

Image-based disease detection

Image-based disease detection signifies the most extensively examined application of AI in plant pathology. Digital images of infected plant organs, particularly leaves, captured using smartphones, digital cameras, or field imaging devices serve as primary inputs for convolutional neural network (CNN)-based classification models [12]. Disease symptoms which include chlorosis, necrosis, lesions, mosaic patterns, and deformities are quantitatively diagnosed through hierarchical feature extraction. Several findings have reported high diagnostic accuracy using deep CNN architectures such as AlexNet, VGGNet, ResNet, and EfficientNet trained on publicly available datasets such as PlantVillage.

Hyperspectral and multispectral imaging

Hyperspectral and multispectral imaging technologies provide enhanced capability for early disease detection by capturing reflectance signatures across multiple wavelengths beyond the visible spectrum. Physiological changes linked with pathogen infection, involving alterations in chlorophyll content, water status, and cellular structure, can be detected prior to the appearance of visible symptoms. Machine learning algorithms applied to spectral datasets enable differentiation of disease-specific signatures, facilitating early diagnosis and targeted disease management [13]. Integration of spectral imaging with AI models has supported high sensitivity in detecting fungal, bacterial, and viral infections at early growth stages.

https://doi.org/10.61577/jpri.2024.100007

UAV and drone-based surveillance

Unmanned Aerial Vehicles (UAVs) equipped with high-resolution RGB, multispectral, or thermal sensors have enabled large-scale monitoring of crop health across broad agricultural fields. AI-based image analysis facilitates automated identification of disease hotspots and spatial distribution of infection severity. UAV-assisted surveillance supports precision agriculture practices by allowing real-time disease mapping and targeted pesticide application [14].

Pre-symptomatic detection

Developing AI approaches focus on pre-symptomatic disease revealing through integration of imaging, biochemical, and environmental datasets. Machine learning models trained on physiological indicators such as pigment variation, canopy temperature, fluorescence signals, and metabolic profiles enable prediction of disease onset before visible symptom development [15]. Coupling AI algorithms with Internet of Things (IoT)-enabled sensors acknowledges continuous crop monitoring and early warning systems, improving decision-making efficiency and reducing yield losses.

AI in Crop Management

Artificial Intelligence (AI) has significantly increased its role in agriculture beyond disease identification toward integrated crop management strategies that increase productivity, resource efficiency, and environmental sustainability. By adding multi-source datasets such as climatic variables, soil properties, crop phenology, and remote sensing inputs, AI-driven models assist predictive and prescriptive decision-making frameworks for precision agriculture [16].

Yield prediction models

Machine learning algorithms have been widely used for crop yield prediction by integrating historical yield records with environmental and agronomic variables, including temperature, precipitation, soil fertility parameters, and vegetation indices. Techniques such as Random Forest, Gradient Boosting, Artificial Neural Networks, and deep learning architecture have shown high predictive capability for crop productivity estimation. These predictive analytics tools enable optimized resource allocation, crop selection strategies, and improved agricultural planning under variable climatic conditions.

Smart irrigation systems

AI-based irrigation management systems utilize sensor-derived soil moisture data, evapotranspiration rates, and weather forecasts to verify optimal irrigation schedules. Machine learning models assist dynamic prediction of crop water requirements, thereby improving water-use efficiency and minimizing excessive irrigation [17]. Addition of IoT enabled sensors with AI algorithms supports automated irrigation scheduling, contributing to sustainable water resource management in water-limited agroecosystems.

Integrated pest management (IPM)

AI-driven pest identification systems based on computer vision techniques allow fast detection of pest infestation using field images and sensor-based monitoring systems. Predictive models including climatic parameters and pest population dynamics provide early warning systems that support timely intervention. These approaches significantly reduce dependency on chemical pesticides, promoting environmentally sustainable pest management practices [18].

Soil health monitoring

Machine learning approaches have been applied for prediction of soil nutrient status, organic carbon content, and physicochemical properties using proximal sensing and remote sensing data [19]. AI-enabled soil fertility mapping supports site-specific nutrient management, improving crop productivity while minimizing extreme fertilizer application.

Weather-adaptive decision support systems

AI-based decision support systems adding meteorological datasets with crop growth models facilitate risk prediction for disease outbreaks, drought stress, and yield variability. These systems assist farmers in applying adaptive agronomic practices aligned with dynamic environmental conditions.

Challenges and Limitations

One of the major challenges is the limited availability of high-quality annotated datasets, specifically for rare diseases and underrepresented crops. Most publicly available datasets are developed under controlled laboratory conditions, resulting in reduced model strength when applied to heterogeneous field environments characterized by varying illumination, background noise, plant growth stages, and symptom variability. Such data heterogeneity across geographical regions affects the generalization capability of trained models.

Deep learning models also demand substantial computational sources, including high-performance GPUs and large storage capacity, which limits availability in resource-constrained agricultural settings. Utilization on mobile and edge devices remains challenging due to memory, power, and limitations. Another significant limitation is the lack of transparency of deep learning algorithms, often referred to as the “black-box” problem, which reduces user confidence in decision-making outputs [20]. Explainable Artificial Intelligence (XAI) approaches are therefore essential to improve transparency and reliability.

Additionally, practical adoption is constrained by socio-economic factors such as limited digital literacy among farmers, high implementation costs, and inadequate infrastructure in developing regions. Addressing these challenges involves interdisciplinary collaboration for developing scalable, cost-effective, and interpretable AI-based agricultural solutions.

Future Directions

Explainable Artificial Intelligence (XAI) approaches are expected to increase the transparency of model predictions through visualization techniques such as saliency maps and heatmaps, allowing better understanding of disease-specific symptom recognition. Edge AI deployment of resource-efficient devices, which include smartphones and embedded sensors, will enable real-time disease diagnosis with minimal latency, increasing accessibility in field conditions [21]. Integration of multi-modal datasets combining imaging, soil physicochemical properties, climatic variables, and genomic information is anticipated to improve predictive accuracy and robustness of disease forecasting models. Additionally, federated learning frameworks provide privacy-preserving collaborative training mechanisms, enabling institutions to share model parameters without exchanging raw datasets. The convergence of AI with IoT-enabled sensors, autonomous drones, and smart farming platforms is expected to build a comprehensive precision agriculture ecosystem supporting sustainable crop productivity.

https://doi.org/10.61577/jpri.2024.100007

Conclusion

AI has emerged as a powerful tool in plant pathology and precision agriculture, significantly improving the accuracy, efficiency, and scalability of plant disease discovery and crop management systems. The addition of deep learning models, computer vision, and remote sensing technologies allows rapid identification of disease symptoms, early stress detection, and improved prediction of crop productivity. AI-based decision-support systems contribute to enhanced irrigation management, pest control strategies, and soil health monitoring, thereby enhancing resource-use efficiency and supporting sustainable agricultural practices.

Effective implementation of AI-driven agricultural solutions needs interdisciplinary collaboration among plant scientists, agronomists, AI researchers, engineers, and policymakers to ensure technical reliability and practical applicability. The availability of robust and diverse datasets remains vital for improving model generalization across crops and agro-climatic conditions. Also, the development of Explainable Artificial Intelligence (XAI) approaches is important to enhance transparency and user confidence in predictive systems.

Future research should focus on cost-effective deployment strategies, edge-compatible computational models, and integration of multi-source agricultural data to improve predictive performance. AI technologies offer significant potential to advance sustainable crop management and strengthen global food security through data-driven agricultural decision-making.

Disclosure Statement

No potential conflict of interest was reported by the authors.

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