Plant Archives Vol. 26, No. 1, 2026 pp. 2431-2438 e-ISSN:2581-6063 (online), ISSN:0972-5210

Plant Archives

Journal homepage: http://www.plantarchives.org
DOI Url : https://doi.org/10.51470/PLANTARCHIVES.2026.v26.no.1.337

PLANT DISEASE DETECTION USING ARTIFICIAL INTELLIGENCE: CURRENT TRENDS AND FUTURE PROSPECTS

Vicky Yadav[1]*, Sharanabasav Huded[2] and Shivkumar Mahadeo Wararkar[3]
[1]Agriculture, Horticulture Fruit science, School of Agriculture, Sanskaram University, Kheri Taluka, Pataude, Jhajjar (HR)124108
[2]Plant Pathology Department, Agricultural College, Warangal, Professor Jayashankar Telangana Agricultural University (PJTAU), Rajendranagar, Hyderabad - 500 030, Telangana, India
[3]Department of Floriculture and Landscape Architecture, Dr. Panjabrao Deshmukh Krishi Vidyapeeth, Akola, Maharashtra-444104, India
*Corresponding Author: vickyrao1282002@gmail.com

(Date of Receiving : 01-02-2026; Date of Revision : 10-03-2026; Date of Acceptance : 19-04-2026)

ABSTRACT

Plant diseases remain a big menace to agricultural productivity in the world, resulting into massive loss of produce, and compromised food security especially in areas experiencing resource shortages. Traditional methods of disease detection that are mostly reliant on expert visual evaluation are slow, subjective, and lack scalability. Over the past few years, the advent of the artificial intelligence (AI) and in particular, machine learning and deep learning algorithms have revolutionized the diagnostics of plant diseases by allowing the detection of the diseases through automated image-based methods at a high accuracy. Convolutional neural networks and computer vision technologies have demonstrated good potential to detect intricate patterns of diseases and facilitate precision farming. This review will critically analyze the advances in AI-driven plant disease detection to date, including the leading models, datasets, and performance trends. It was systematically and interpretively based on the methodological approach relying on the peer-reviewed literature of significant academic databases. It is emphasized in the analysis that deep learning models, and CNN-based architectures, in particular, and transfer learning training, in particular, are prevalent in the field and often achieve high accuracy when trained in controlled settings on benchmark datasets. Nevertheless, the review also notes the major limitations, such as the bias of the data set, low generalizability to real-life scenarios, high computational costs, and the absence of interpretability of the so-called black-box models. Such obstacles limit the applicability and adoption scale of AI solutions, particularly among the smallholder farmers. Moving forward, the evolution of multiple, field based datasets, explainable AI integration to enhance greater transparency, and edge computing to implement real time, on field diagnosis should be the focus of future research. It will also be necessary to strengthen the institutional support and digital infrastructure to close the technology development and practical application to achieve sustainable and inclusive agricultural transformation.

***Keywords* :** Artificial intelligence, plant diseases, deep learning, image analysis, precision agriculture.

Introduction

Background and Significance

Plant diseases have been one of the biggest limitations to agricultural productivity globally, resulting in massive loss of yield, and posing a threat to food security, especially in the developing economies. Timely and proper diagnosis is thus paramount in managing the disease and in the production of crops sustainably. Nevertheless, traditional diagnostic methods, mostly depending on visual examination of specialists, are sometimes time-consuming, subjective and have restricted capacity due to the presence of qualified staff. In addition, the similarity of the symptoms in various diseases and environmental variations make it even more difficult to identify exactly (Barbedo, 2016). These constraints note the necessity of scalable, objective and quick diagnostic solutions.

The advent of AI in Agriculture

Artificial intelligence (AI) and especially machine learning and deep learning have considerably changed the way plant diseases are detected. Models based on AI in particular convolutional neural networks (CNNs) have proven to be very competent in identifying the complex patterns in leaf images and diagnosing the diseases with a high degree of accuracy (Mohanty *et al*., 2016; Ferentinos, 2018). This change of technology is in line with the larger paradigm of precision agriculture, the use of data-driven technologies to improve decisions and resource efficiency. Moreover, the development of transfer learning and cloud-based systems has allowed to implement the disease detectors on mobile devices, which allows to diagnose the disease in real-time and in the field (Chen *et al*., 2020; Picon *et al*., 2019). The cross-linking of AI and Internet of Things (IoT) technologies is also broadening the boundaries to automated and continuous monitoring of crops (Dhaka *et al*., 2023).

Problem Statement

Even though a lot of progress has been made, there are a number of serious challenges which impede the implementation of the AI-based plant disease detection systems. First, in the real-world environment, the accuracy of models tends to decrease because of different light levels, background noise, and image quality, which means that they can hardly be generalized to other datasets (Abade *et al*., 2021). Second, scalability is a problem with most models being trained on particular crops or diseases and not adaptable to a variety of agricultural settings. Third, there are restrictions to accessibility, including poor digital infrastructure, high computational costs, and poor technical literacy among smallholder farmers, hindering practical implementation (Ibrahimi and Akchioui, 2023). Moreover, the opaque character of the deep learning models is an issue that appears to be a problem in terms of interpretability and trust by users (Hasan *et al*., 2020).

Objectives of the Review

With these issues in mind, the current review will critically review the use of AI methods in the detection of plant diseases. It aims to assess the performance and constraints of all kinds of models, but especially deep learning architectures. Moreover, the review will seek to discover new trends, such as the introduction of IoT, hyperspectral imaging, and edge computing, which are influencing the next-generation diagnostic systems (Kuswidiyanto *et al*., 2022; Talaat *et al*., 2026). Through evidence synthesis, this research also identifies the gaps in existing research such as the diversity of datasets, validation on the field, and model explainability and suggests future research directions. Finally, the review aims to help develop more resilient, convenient, and scalable AI-based solutions to sustainable plant disease management.

Review Design

The proposed research takes the form of a systematic but critically interpretive review research design since it seeks to synthesize the existing knowledge on the use of artificial intelligence (AI) in the detection of plant diseases. In contrast to fully descriptive reviews, a critical stance was used to not just summarize previous research, but also challenge its methodological soundness, applicability and limitations. Structured literature identification and qualitative assessment are combined in the design, allowing an equal evaluation of technological advances and their applicability in practice. The methodological orientation is based on the previous extensive reviews in the field, which stress the necessity of systematic synthesis as the deep learning studies in the field are growing at a very rapid rate (Abade *et al*., 2021; Upadhyay *et al*., 2025). Moreover, the knowledge acquired in the literature on AI also shows the impact of changing architectures on agricultural applications, which require critical evaluation at all times (LeCun *et al*., 2015).

Data Sources and Search Strategy

To guarantee extensive and impartial coverage of the relevant literature, a multi-database search strategy was used. The systematic search was made in major academic repositories, such as Scopus, Web of Science, and Google Scholar. These databases were chosen because they have extensive indexing of high-impact journals in the fields of agriculture, computer science, and interdisciplinary fields. The search algorithm involved the development of specifically designed Boolean search terms, which included a combination of terms, including plant disease detection, artificial intelligence, deep learning, machine learning, and computer vision. Differences and synonyms were added to represent the different terminologies that are used in different researches. As an example, such combinations as AI AND crop disease identification and CNN OR deep learning AND plant pathology were used. This choice was informed by previous reviews that revealed the significance of comprehensive, inclusive, mapping of keywords to encompass the diversity in technologies in AI-based plant diagnostics (Hasan *et al.*, 2020; Ibrahimi and Akchioui, 2023). Also, new topics like the integration of IoT and hyperspectral imaging were included in the search terms to capture new trends (Dhaka *et al.*, 2023; Kuswidiyanto *et al.*, 2022).

Inclusion and Exclusion Criteria

In order to ensure the scientific rigor and relevance, clear inclusion and exclusion criteria were specified. The review will mostly concentrate on the research that was published not more than ten years (20152026) ago, which was a time when deep learning and its use in agriculture made a significant breakthrough. Nevertheless, some seminal work was added to give conceptual basis. Peer reviewed journal articles and conference proceedings of high quality were included among eligible studies to guarantee methodological soundness and credibility. Studies focused on image-based disease detection, creating models, or diagnostic systems that used AI were prioritized. On the other hand, any study that was non-peer reviewed, not clearly reported on methods used, or not related to plant disease detection directly were eliminated. Those articles that only addressed irrelevant agricultural technologies devoid of a diagnostic aspect were also excluded. In addition, research that lacked sufficient experimental evidence or poorly defined data were also subject to critical analysis or filtering, as previous criticism has noted about the data biases and difficulty in reproducibility (Barbedo, 2016; Xu *et al.*, 2024).

Data Extraction and Synthesis

An organized data mining system was used to systematically categorize data of the selected studies. The most important variables were the type of AI method (e.g., CNN, SVM, transfer learning), crop or disease target, characteristic of the data, and performance measures and the context of application. This classification facilitated cross-comparison of the methodologies and results. Thematic grouping was used in the synthesis process together with critical evaluation. Research papers were categorized according to prevailing models like classical machine learning, deep learning models, and hybrid systems with IoT or robotics. The efficiency of the models, their scalability, and on-the-job deployment were compared. To illustrate, although deep learning models are highly accurate in controlled settings (Ferentinos, 2018; Mohanty *et al.*, 2016), they tend to ruin their performance in the field because of the varying light intensity and surrounding noise (Picon *et al.*, 2019; Saleem *et al.*, 2019). A critical framework was also used to evaluate the strengths, limitations as well as gaps in research such as overfitting, lack of dataset diversity as well as insufficient interpretability. Newer technologies like transfer learning and edge-based AI systems were also considered as having the potential to solve these issues (Chen *et al.*, 2020; Talaat *et al.*, 2026). On the whole, this integrative approach will make sure that the review does not focus on integration of the results but provides a critical and insight-based synthesis of findings that will reveal what progress has been made and what gaps still need to be closed to make AI-based plant disease management sustainable.

Overview of AI Techniques in Plant Disease Detection

Introduction to AI Methods in Detection of Plant Disease.

Plant disease detection using artificial intelligence has developed beyond the traditional machine learning (ML) architectures to more advanced deep learning (DL) architectures. Initial methods, Support Vector Machines (SVM), Randome Forest, and K-Nearest Neighbors (KNN), were highly dependent on handcrafted features, such as color, texture, and shape descriptors, and so they could not easily adapt to varied crop conditions (Barbedo, 2016). The introduction of deep learning, specifically, Convolutional Neural Networks (CNNs) enabled the extraction of features automatically, increasing the accuracy and scalability of classification (LeCun *et al.*, 2015; Mohanty *et al.*, 2016). State-of-the-art architectures, such as Recurrent Neural Networks (RNNs) and Transformers, are also being investigated in the context of temporal and contextual analysis. Hybrid and ensemble models further improve the robustness of the model, by integrating various algorithms, lessening model bias and improving predictive performance (Upadhyay *et al.*, 2025).

The sources of data and datasets will be described as follows: The quality and diversity of datasets are intrinsically connected to the performance of AI models. Open datasets like Plant Village have been used to set baseline performance of models (Mohanty *et al.*, 2016). Nevertheless, these datasets are mostly controlled in laboratories, with homogeneous backgrounds and perfect lighting scenarios, which are not representative of the real world. Field-based datasets, which are more realistic, bring in variability in illumination, occlusion, and disease stage, which is difficult to generalize in models (Xu *et al.*, 2024). The skew associated with data imbalance, where some diseases are overrepresented, also further skews model performance, which tends to provide biased predictions. As a consequence, the difference between laboratory success and practical use is a pressing issue.

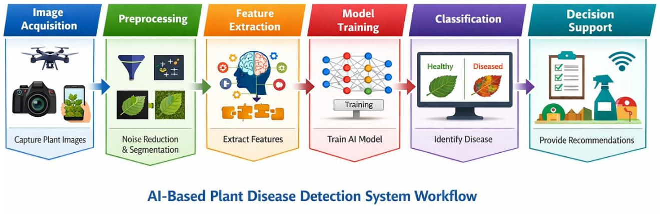

Fig. 1 : General steps of an artificial intelligence-based system of plant disease detection indicating the sequence of steps such as image acquisition, preprocessing, feature extraction, model training, classification, and decision support.

Deep learning was also a breakthrough as it allowed extracting features automatically and performing better classification (LeCun *et al.*, 2015). CNNs have shown a higher level of accuracy in detecting plant diseases in different crops (Ferentinos, 2018; Saleem *et al.*, 2019).

Performance Evaluation Metrics

Accuracy, precision, recall and F1-score are the common metrics used in most studies to report performance. Although high accuracy rates, which are often over 95 percent, are often cited in controlled environments, such values could be misleading when models are used in heterogeneous environments (Ferentinos, 2018). Precision and recall give a more accurate understanding of model reliability especially in the differentiation of similar disease symptoms. Nevertheless, little focus is on real-world validation, where there is great variability in the environment and unknown data that have a great impact on performance. Therefore, the necessity to focus on strength and ex-post control is becoming more important compared to the strictly experimental measurements.

Table 1 : Overview of AI Methods in Detection of Plant Disease.

AI Technique	Methodology/Approach	Application in Plant Disease Detection	Key Findings	References
Machine Learning (ML)	SVM, Random Forest, KNN with handcrafted features	Classification of diseased vs healthy leaves	Moderate accuracy; depends on feature engineering	Barbedo (2016); Wang *et al.* (2017)
Convolutional Neural Networks (CNNs)	Deep learning-based automatic feature extraction	Image-based disease identification across crops	High accuracy (>95%) under controlled conditions	Mohanty *et al.* (2016); Ferentinos (2018); Saleem *et al.* (2019)
Transfer Learning	Fine-tuning pre-trained models (e.g., AlexNet, VGG)	Reduces training data requirement	Improved efficiency and faster convergence	Too *et al.* (2019); Chen *et al.* (2020)
Deep Neural Networks (DNNs)	Multi-layer neural architectures	Recognition of complex disease patterns	Better performance than traditional ML	Sladojevic *et al.* (2016); Brahimi *et al.* (2017)
Hyperspectral Imaging + AI	Spectral data integrated with CNN models	Detection of early-stage and hidden diseases	High precision due to spectral sensitivity	Kaya and Gürsoy (2025)
Lesion-based Detection Models	Focus on disease spots and infected regions	Accurate identification at micro-level	Improves disease localization	Barbedo (2019)
IoT + AI Systems	Sensors + cloud-based AI analysis	Real-time crop monitoring and disease alerts	Enables precision agriculture	Dhaka *et al.* (2023); Ibrahim *et al.* (2023)
Mobile-based AI Applications	Smartphone image capture + AI models	Field-level disease diagnosis by farmers	Cost-effective and user-friendly	Picon *et al.* (2019); Xu *et al.* (2024)
AI-based Robotics	Autonomous robots with vision systems	Automated disease detection and crop management	Reduces labor dependency	Talaat *et al.* (2026)
Hybrid AI Models	Combination of ML, DL, and IoT	Integrated disease detection systems	Improved robustness and scalability	Upadhyay *et al.* (2025);

Comparative Analysis of Models

Comparative studies indicate that deep learning models and particularly CNN-based architectures are always more accurate and automatized with respect to traditional ML models (Saleem *et al.*, 2019). Nonetheless, it does at the cost of greater computational complexity and data dependency. ML models are not as accurate, but are computationally efficient and more interpretable. Transfer learning methods have become a trade-off so that, they can achieve high performance with less training data (Chen *et al.*, 2020). However, accuracy/speed/resource trade-offs continue to dominate model choice, especially when it is used in resource-constrained agricultural systems.

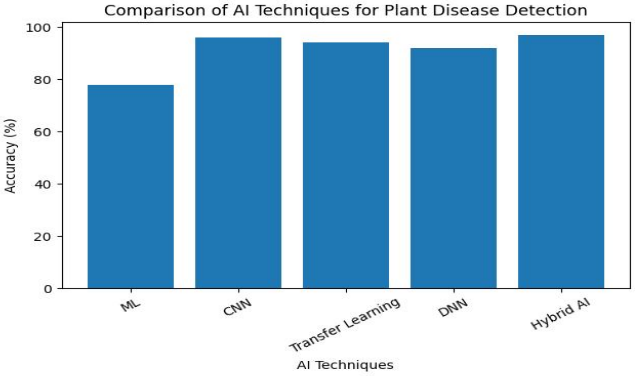

Fig. 2 : Comparative analysis of the various artificial intelligence methods in identification of plant diseases and emphasize that deep learning and hybrid methods have high accuracy over conventional machine learning methods..

Major Trends and New Technologies.

The recent development also shows a move towards real-time and integrated disease detecting systems. On-field diagnosis can be done with the assistance of mobile-based applications, and AI tools are more affordable to farmers (Picon *et al.*, 2019). The combination of AI and Internet of Things (IoT) devices and drones will enable the extensive surveillance and prior disease identification (Dhaka *et al.*, 2023). Hyperspectral imaging and robotics are part of emerging systems as well to achieve precision in agriculture (Kuswidiyanto *et al.*, 2022; Talaat *et al.*, 2026). The innovations are signs of the shift of isolated diagnostic tools to the multi-faceted decision-support systems.

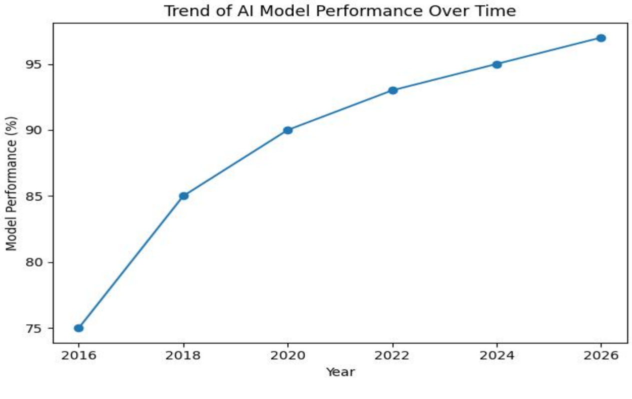

Fig. 3 : Temporal trend that demonstrates the enhancement of the performance of artificial intelligence models to detect plant diseases over the period between 2016 and 2026, which implies the ongoing improvements of deep learning and hybrid methods.

Moreover, artificial intelligence that will be implemented alongside smart agricultural systems, such as IoT and robotics, will transform the way diseases are handled (Ibrahimi *et al.*, 2025). Real-time decision support and detection systems will be essential in increasing the productivity and sustainability of crops.

Important Problems and Constraints

Although a lot has been done, there are a number of constraints. One of the key challenges is overfitting, especially when the model is trained on a small or homogenous set of data (Hasan *et al.*, 2020). The absence of thorough field validation demeans the confidence in real-life application. Moreover, deep learning models are black-box in nature, which can be a cause of interpretability and trust issues among end-users. Another essential issue is accessibility, whereby smallholder farmers may not have the infrastructure or technical expertise and financial means to use these technologies (Barbedo, 2019). The drawbacks demonstrate the necessity of more considerate and inclusive AI solutions.

Socio-Economic and Practical Implications

There is a disparity in the use of AI-based disease detection systems especially in developing countries. The high cost of implementation, the lack of digital infrastructure, and a low level of technical literacy are among the key obstacles (Ibrahimi and Akchioui, 2023). Moreover, the performance of such systems is based on the localized adaptation, which is not always the case. It can only be bridged through the use of technological innovation as well as institutional support, capacity building and policy interventions. Finally, the effectiveness of AI in detecting plant diseases will rely on its capacity to meet the socio-economic realities of end-users and provide reliable and scalable solutions.

Future Prospects

The future of artificial intelligence-based plant disease detection is more geared towards enhancing transparency, scalability, and applicability in the real world. Despite the high accuracy of deep learning in controlled settings, the next step of progress is to fill the gaps that are critical like interpretability, data variety, system integration, and institutional support. One of the key new trends is the introduction of Explainable Artificial Intelligence (XAI) to improve the transparency and trust in AI-based diagnostics. The majority of deep learning models, especially convolutional neural networks, are black boxes, and therefore, users can hardly comprehend the process of making decisions. This is not interpretable, a fact that restricts their adoption by farmers and agricultural experts. Saliency maps and feature visualization are some techniques that can be used to highlight the disease-affected areas on the plant pictures, and thus, make the model outputs more interpretable (Brahimi *et al*., 2017; Hasan *et al*., 2020). To increase trust in the user, as well as to enhance model validation and error analysis, it is necessary to enhance explainability, particularly in complex field conditions (Kaya & Gursoy, 2025). The other potential direction is the combination of AI and Internet of Things (IoT), robotics, and cloud computing. The combination of the technologies allows real-time monitoring, automated disease detection and decision support systems. The IoT sensors are capable of continuously monitoring parameters of the environment e.g. humidity, temperature, and soil conditions which are vital in predicting diseases. These systems can offer location-specific recommendations in time with the help of AI algorithms that can be implemented on the cloud (Dhaka *et al*., 2023). Moreover, AI models and sensors on the imaging of crops installed on robots can autonomously scan the crops and identify diseases early on, eliminating the necessity of manual scanning (Talaat *et al*., 2026). These integrated systems are a transition to intelligent and autonomous agro ecosystems. Another key requirement is the need to develop large, diverse and real-world datasets in order to continue making progress. Most current AI models are trained on curated datasets like PlantVillage, which tend to be of images taken under controlled conditions. Although these datasets have proven to be very useful in research, they are not reflective enough of the variability experienced in the real agricultural setting such as variations in lighting, background and severity of disease (Mohanty *et al*., 2016; Xu *et al*., 2024). Consequently, these datasets tend to cause models trained on them to not generalize well in the field. The development of large-scale and annotated datasets that can reflect a variety of crops, diseases, and environmental conditions should be a priority in future studies. Joint efforts in data-sharing and crowd-sourced data might be crucial in this respect (Abade *et al*., 2021). Concurrently, Edge AI is becoming a ground-breaking technology used to diagnose on-field diseases. In contrast to cloud-based systems, edge computing allows processing of data directly on the device, e.g., smartphone, drone, or embedded systems. This lowers the latency, lowers reliance on the internet connection and makes decisions faster in secluded or resource constrained locations. Disease detection apps are already used on mobile, showing the promise of implementing lightweight deep learning-based models to diagnose a disease in real-time (Picon *et al*., 2019). With the increase in hardware capabilities, edge AI systems will become more efficient, precise and reachable especially to smallholder farmers in developing areas.

Lastly, policy frameworks and institutional support are crucial to the widespread adoption of AI-driven plant disease detection systems. Though technological innovations have been made, challenges like high implementation, the absence of digital infrastructure, and technical knowledge still present reasons that restrain adoption (Barbedo, 2016; Upadhyay *et al*., 2025). Governments and agricultural institutions should be proactive through promoting digital literacy, research, and development and the establishment of partnerships between the public and the private. There are additional policies that can be implemented to speed up innovation and adoption: open access to data and standardization, along with ethical use of AI. Also, extension services should be enhanced to overcome the gap between technological development and implementation at the level of the farmers. In conclusion, the future of AI in detecting plant diseases will be in the creation of transparent, integrated, and ready-to-use systems with robust datasets and facilitating policy conditions. The dimensions will be important in meeting the challenge of translating the technological potential to sustainable agricultural impact.

Conclusion

This review summarizes the fast development of artificial intelligence in the field of plant disease detection, and there is a distinct shift towards complex deep learning models, as opposed to traditional machine learning methods. Convolutional neural networks and transfer learning have shown great diagnostic accuracy especially in controlled conditions and integrated systems that combine AI with IoT, mobile platform and robotics have extended the functional range to real time and automated crop monitoring. All these findings suggest that AI can greatly contribute to revolutionizing plant health management by enhancing disease diagnosis speed, accuracy, and scale. Nonetheless, a critical reflection shows that there is a consistent disconnect between the experimental success and applicability on the field level. Most AI systems still use curated datasets with low diversity, leading to lower generalization with real-world conditions of varying lighting, complicated backgrounds, and varying manifestations of a disease. Moreover, challenges like the lack of interpretability in models, expensive computational costs, and inaccessibility by smallholder farmers hinder large-scale adoption. The lack of transparency and trust, as a prerequisite to practice, of deep learning models, in particular, is of concern due to their black-box characteristics. The problem of closing the research-practice gap thus becomes one of the priorities. The next generation of work should be taking a step past accuracy-oriented development of models to context-sensitive, user-focused solutions. It involves building heterogeneous, field-representative data, integration of explainable AI methods and building lightweight models that can be deployed on edge devices. It is also crucial to enhance the institutional processes like agricultural extension services, digital literacy programs, and policy support to enable technology dissemination and adoption to the grassroots level. In the future, the key to sustainable AI-based plant health management lies in the ability to combine technological innovation and socio-economic realities. To make AI solutions accessible, affordable, and scalable, a multidisciplinary approach with researchers, policymakers, and farmers is necessary to ensure that AI solutions are not only technically sound but also accessible, affordable, and scalable. Provided that the challenges are mitigated in a strategic manner, AI can emerge as a foundation of reliable and sustainable agro-ecosystems in the future.

Acknowledgements

The authors also recognize that their respective institutions assisted them to have all the required resources and academic setting to conduct this study. Other organizations and databases that made access to the relevant literature and research materials accessible in this review are also appreciated. This study did not get any external funding. The authors are grateful to their respective institutions to have given them the academic support and access to the resources needed to accomplish this work.

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