REVISTA CIENTÍFICA - RECIMA21 ISSN 2675-6218

ARTIFICIAL INTELLIGENCE FOR PLANT DISEASE DETECTION, MONITORING, AND FORECASTING: ADVANCES, CHALLENGES, AND FUTURE GAPS

INTELIGÊNCIA ARTIFICIAL PARA DETECÇÃO, MONITORAMENTO E PREVISÃO DE DOENÇAS DE PLANTAS: AVANÇOS, DESAFIOS E LACUNAS FUTURAS

INTELIGENCIA ARTIFICIAL PARA LA DETECCIÓN, EL SEGUIMIENTO Y LA PREDICCIÓN DE ENFERMEDADES DE LAS PLANTAS: AVANCES, DESAFÍOS Y LAGUNAS FUTURAS

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e757842
https://doi.org/10.47820/recima21.v7i5.7842

PUBLISHED: 05/2026

ABSTRACT

Plant diseases are one of the main limiting factors in global agricultural productivity, causing significant losses and compromising food security. The increasing complexity of production systems and the limitations of traditional diagnostic methods, based mainly on visual assessment and laboratory analyses, have driven the incorporation of artificial intelligence (AI) in plant pathology. In this context, the present study aimed to synthesize the advances, challenges, and gaps related to the application of AI in the detection, monitoring, and forecasting of plant diseases. This is an integrative literature review, conducted through systematic searches in national and international scientific databases, encompassing studies that addressed machine learning techniques, deep learning, and hybrid models applied to plant pathology. Approaches based on RGB images, multispectral and hyperspectral data, integration with unmanned aerial vehicles (UAVs), and forecasting models based on climatic variables were analyzed. The results show that convolutional neural networks and temporal architectures, such as LSTM, have substantially increased the diagnostic accuracy and forecasting potential of the systems, especially when integrated with environmental data. However, challenges persist related to the generalization of the models, scarcity of representative databases, field variability, and high computational cost. It is concluded that AI represents a strategic tool for the transition from a reactive phytopathology to a predictive and decision-support approach. However, its consolidation under real cultivation conditions depends on robust agronomic validation, methodological standardization, and multidisciplinary integration, aiming at more precise, sustainable systems applicable to precision agriculture.

KEYWORDS: *Digital plant pathology. Predictive modeling. Precision agriculture. Deep learning.*

RESUMO

As doenças de plantas constituem um dos principais fatores limitantes da produtividade agrícola global, ocasionando perdas significativas e comprometendo a segurança alimentar. A crescente complexidade dos sistemas produtivos e as limitações dos métodos tradicionais de diagnóstico, baseados majoritariamente na avaliação visual e em análises laboratoriais, têm impulsionado a incorporação da inteligência artificial (IA) na fitopatologia. Nesse contexto, o presente estudo teve como objetivo sintetizar os avanços, desafios e lacunas relacionadas à aplicação da IA na detecção, monitoramento e previsão de doenças de plantas. Trata-se de uma revisão integrativa da literatura, conduzida a partir

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de buscas sistemáticas em bases científicas nacionais e internacionais, contemplando estudos que abordaram técnicas de machine learning, deep learning e modelos híbridos aplicados à fitopatologia. Foram analisadas abordagens baseadas em imagens RGB, dados multiespectrais e hiperespectrais, integração com veículos aéreos não tripulados (UAVs) e modelos preditivos fundamentados em variáveis climáticas. Os resultados evidenciam que redes neurais convolucionais e arquiteturas temporais, como LSTM, ampliaram substancialmente a acurácia diagnóstica e o potencial preditivo dos sistemas, especialmente quando integradas a dados ambientais. Entretanto, persistem desafios relacionados à generalização dos modelos, escassez de bases de dados representativas, variabilidade de campo e elevado custo computacional. Conclui-se que a IA representa ferramenta estratégica para a transição de uma fitopatologia reativa para uma abordagem preditiva e de suporte à decisão. Todavia, sua consolidação em condições reais de cultivo depende de validação agronômica robusta, padronização metodológica e integração multidisciplinar, visando sistemas mais precisos, sustentáveis e aplicáveis à agricultura de precisão.

PALAVRAS-CHAVE: Fitopatologia digital. Modelagem preditiva. Agricultura de precisão. Aprendizado profundo.

RESUMEN

Las enfermedades de las plantas constituyen uno de los principales factores limitantes de la productividad agrícola mundial, causando pérdidas significativas y comprometiendo la seguridad alimentaria. La creciente complejidad de los sistemas de producción y las limitaciones de los métodos de diagnóstico tradicionales, basados principalmente en la evaluación visual y los análisis de laboratorio, han impulsado la incorporación de la inteligencia artificial (IA) en la fitopatología. En este contexto, el presente estudio tuvo como objetivo sintetizar los avances, los desafíos y las lagunas relacionados con la aplicación de la IA en la detección, el monitoreo y la predicción de enfermedades de las plantas. Se trata de una revisión bibliográfica integradora, realizada mediante búsquedas sistemáticas en bases de datos científicas nacionales e internacionales, que abarca estudios que abordan técnicas de aprendizaje automático, aprendizaje profundo y modelos híbridos aplicados a la fitopatología. Se analizaron enfoques basados en imágenes RGB, datos multiespectrales e hiperespectrales, la integración con vehículos aéreos no tripulados (VANT) y modelos predictivos basados en variables climáticas. Los resultados muestran que las redes neuronales convolucionales y las arquitecturas temporales, como LSTM, han aumentado sustancialmente la precisión diagnóstica y el potencial predictivo de los sistemas, especialmente cuando se integran con datos ambientales. Sin embargo, persisten desafíos relacionados con la generalización de los modelos, la escasez de bases de datos representativas, la variabilidad del campo y el alto costo computacional. Se concluye que la IA representa una herramienta estratégica para la transición de una fitopatología reactiva a un enfoque predictivo y de apoyo a la toma de decisiones. No obstante, su consolidación en condiciones de cultivo reales depende de una validación agronómica sólida, la estandarización metodológica y la integración multidisciplinaria, con el objetivo de lograr sistemas más precisos y sostenibles aplicables a la agricultura de precisión.

PALABRAS CLAVE*: Fitopatología digital. Modelado predictivo. Agricultura de precisión. Aprendizaje profundo.*

INTRODUCTION

Plant diseases are among the main constraints to global agricultural productivity, causing substantial reductions in food production and directly affecting food security. Estimates indicate that diseases caused by fungi, bacteria, viruses, and nematodes are responsible for losses ranging from 10 to 16% of worldwide agricultural production, reinforcing the need for more efficient strategies for early detection and rational phytosanitary management (Savary *et al.*, 2019; Oerke, 2005). In this

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context, the integration of Artificial Intelligence (AI) into phytopathology emerges as an innovative and promising approach capable of improving diagnostic precision and supporting decision-making processes in increasingly complex agricultural systems (González-Rodríguez *et al*., 2024).

Traditionally, phytopathological diagnosis has relied mainly on visual symptom assessment, empirical knowledge of specialists, and classical laboratory techniques, such as pathogen isolation and morphological identification. Although widely consolidated, these approaches present important limitations, including high subjectivity, dependence on specialized professionals, and reduced efficiency in detecting infections during early stages. According to Uwe Mahlein *et al.* (2024), symptom expression may vary according to cultivar, environmental conditions, and plant phenological stage, which compromises diagnostic accuracy and reduces the effectiveness of disease management strategies.

The development of digital agriculture has stimulated the incorporation of computational approaches as complementary tools to conventional phytopathological methods. Early studies primarily employed classical machine learning algorithms, including k-nearest neighbors, support vector machines, and decision trees, for disease classification based on handcrafted image features. However, the dependence on manual feature extraction limited the robustness and generalization capacity of these models. In recent years, advances in deep learning, particularly through Convolutional Neural Networks (CNNs), have promoted significant improvements in plant disease recognition by enabling the automatic extraction of complex visual patterns directly from images, resulting in higher diagnostic accuracy across different crops (Nyawose; Maswanganyi; Khumalo, 2025).

Simultaneously, improvements in computational capacity and the expansion of high-resolution sensing technologies have broadened the scope of AI applications in phytopathology. Recent studies indicate that deep learning models can integrate RGB imagery, multispectral and hyperspectral information, and environmental variables to identify physiological alterations associated with infections even before visible symptoms appear (Liu; Li; Wang, 2023). In this sense, Garrett *et al.* (2022) emphasize that the integration of environmental and imaging data contributes to the anticipation of phytopathological outbreaks, supporting more sustainable disease management strategies and reducing the indiscriminate use of crop protection products.

More recently, the increasing availability of agricultural big data and the development of hybrid computational models integrating deep learning, climatic variables, and spatial information have substantially expanded the applicability of AI in phytopathology. These systems not only improve disease detection but also enable continuous monitoring and forecasting of epidemiological risk scenarios. Such advances represent a transition from a predominantly reactive phytopathology toward a forecasting-oriented and decision-support approach aligned with the principles of precision

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agriculture and agricultural sustainability, favoring more resilient production systems (Kim & Lee, 2020).

Given this context, Artificial Intelligence has become a strategic tool for the modernization of phytopathology by enabling faster diagnostics, continuous monitoring, and forecasting approaches based on the integration of multiple data sources, acting in a complementary manner to traditional methods already established in the field. Therefore, this review aims to synthesize recent advances, discuss the main methodological challenges, and identify research gaps related to the application of AI in the detection, monitoring, and forecasting of plant diseases, contributing to the development of more robust and applicable systems under real-world agricultural conditions.

METHODOLOGY

This study is characterized as an integrative literature review, conducted through the analysis of previously published scientific productions, including peer-reviewed journal articles, academic books, and technical-scientific documents related to the application of Artificial Intelligence (AI) in phytopathology. The purpose of an integrative review is to gather, systematize, and synthesize existing knowledge on a specific topic, providing a comprehensive overview of the state-of-the-art, identifying trends, scientific advances, methodological limitations, and research gaps, as well as supporting future investigations (Souza; Silva; Carvalho, 2010).

The review was conducted in a systematic and structured manner, aiming to ensure greater methodological rigor, transparency, and reproducibility. The methodological procedure comprised the following stages: (a) definition of the research theme and guiding question, centered on the application of AI techniques for the detection, monitoring, and forecasting of plant diseases; (b) selection of descriptors and scientific databases; (c) establishment of inclusion and exclusion criteria; (d) identification, screening, and eligibility assessment of studies; (e) full-text reading and critical comparative analysis of the selected works; and (f) organization, synthesis, and presentation of the results.

The bibliographic survey included studies published between 2000 and 2025 and was conducted through searches in the following databases and repositories: Google Scholar, Scientific Electronic Library Online (SciELO), the CAPES Periodicals Portal (Coordination for the Improvement of Higher Education Personnel), and digital repositories of academic books and technical-scientific publications. The search strategy employed descriptors in both Portuguese and English, including the following terms: “Artificial Intelligence”, “Plant Diseases”, “Digital Phytopathology”, “Machine Learning”, “Deep Learning”, “Disease Detection”, “Phytosanitary Monitoring”, and “Plant Disease Forecasting”.

The inclusion criteria comprised studies whose titles and abstracts were coherent with the proposed review theme and directly addressed AI applications in plant disease detection, monitoring,

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forecasting, or digital phytopathology. Initially, a preliminary screening of titles and abstracts was performed. Duplicate studies, incomplete publications, and works that did not present thematic adherence to the objectives of the review were excluded. Subsequently, the selected studies underwent full-text reading, enabling a critical evaluation of their methodological approaches, results, scientific relevance, and contributions to the advancement of knowledge in the field of AI-assisted phytopathology.

To improve the robustness of the review, the qualitative evaluation of the included studies considered aspects such as methodological coherence, applicability of AI techniques, consistency of results, and scientific relevance to the field of digital phytopathology. In addition, the study selection process followed systematic stages of identification, screening, eligibility, and inclusion, organized according to a structured review flow, aiming to enhance the reliability and reproducibility of the review process.

CLASSIFICATION OF ARTIFICIAL INTELLIGENCE TECHNIQUES IN PHYTOPATHOLOGY: CLASSICAL MACHINE LEARNING, CONVOLUTIONAL NEURAL NETWORKS, AND HYBRID MODELS

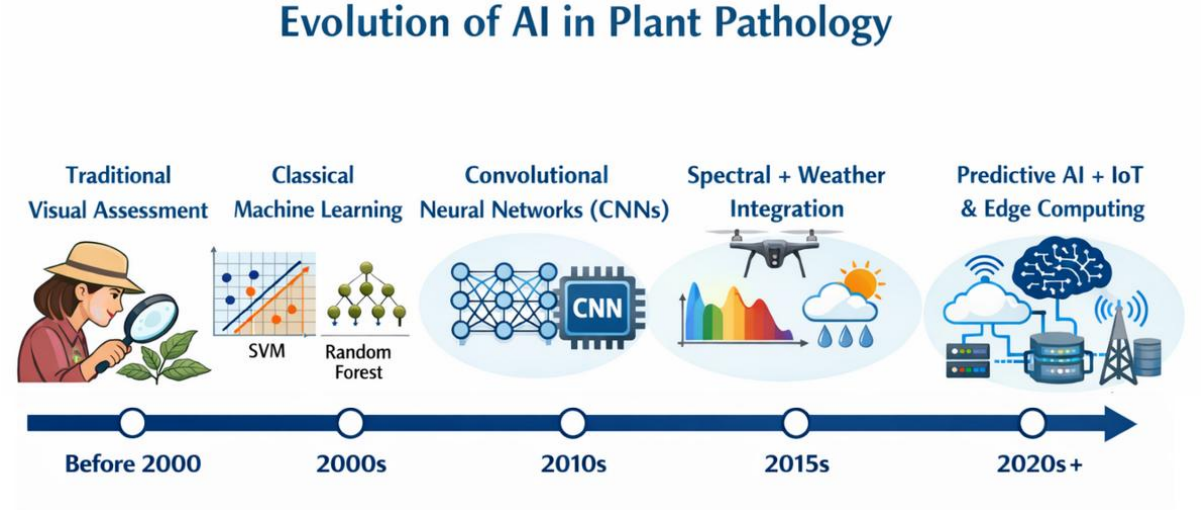
Early applications of Artificial Intelligence in phytopathology were heavily anchored in classical machine learning approaches, which employ statistical algorithms to identify patterns in structured datasets (Tsaftaris *et al.*, 2016). In this initial stage, methods such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), logistic regression, and decision trees were widely used for plant disease classification based on handcrafted features previously extracted from images, including attributes related to texture, coloration, and lesion morphology (Nyawose, Maswanganyi & Khumalo, 2025).

Although these algorithms demonstrated satisfactory performance in controlled environments, their effectiveness proved to be highly dependent on the feature engineering stage. This dependency limited the scalability and robustness of the models when faced with the complexity of real-world agricultural systems (Kim & Lee, 2020). The evolution of approaches employed in phytopathology, ranging from traditional methods to AI-based predictive systems, is summarized in Figure 1.

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Figure 1. Development workflow of phytosanitary diagnostic techniques, highlighting the transition from expert-based methods to high-complexity automated systems



This reliance on predefined attributes proved to be a critical factor when such models were applied under field conditions, characterized by high environmental variability. Indeed, studies have shown that classical machine learning models faced significant constraints regarding their generalization capability across different crops, phenological stages, and variable lighting conditions (Singh *et al.*, 2016; Singh *et al.*, 2018). As pointed out by González-Rodríguez *et al.* (2024), the requirement for manual feature selection makes these algorithms particularly sensitive to noise, reducing their robustness against common agricultural factors such as shading, leaf overlap, and abiotic stresses that can mask or mimic phytopathological symptoms. These limitations highlighted the need for more flexible and adaptive approaches, driving the transition toward deep learning methods.

In this context, Convolutional Neural Networks (CNNs) emerged as a milestone in the application of AI to plant disease detection by enabling the automatic extraction of hierarchical features directly from images, eliminating the dependency on manual feature engineering (Ferentinos, 2018). By learning visual patterns in an end-to-end fashion, CNNs significantly expanded the models' adaptability to different agricultural scenarios. Evidence synthesized by Nyawose, Maswanganyi & Khumalo (2025) indicates that established architectures—such as AlexNet, VGG, ResNet, and EfficientNet—achieve high accuracy rates in identifying foliar diseases across multiple crops, especially when trained on large RGB image datasets, consolidating them as the predominant approach in automated phytosanitary diagnostic systems.

Despite these substantial advances, the adoption of deep learning techniques has not completely eliminated the inherent challenges of AI in phytopathology. As highlighted by Mahlein *et al.* (2024), even deep learning-based models still face limitations related to the interpretation of complex biological data and generalization to real-world field conditions. Although hierarchical learning has

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overcome the need for manual feature extraction, the performance of deep neural networks remains heavily dependent on the availability, diversity, and quality of labeled data, in addition to requiring high computational power to process the visual complexity associated with plant symptoms.

To mitigate these limitations, more recent approaches have explored hybrid models as a strategy to broaden the scope and applicability of AI in phytopathology. These systems combine CNNs with classical machine learning algorithms, additional deep learning techniques, or temporal models, allowing for the integration of multi-source data, such as images, climate variables, and spectral information. Consequently, such models are not restricted to point-in-time disease detection but enable the modeling of disease progression over time, enhancing AI's potential for predictive applications and decision support in Integrated Disease Management (IDM) (Nyawose; Maswanganyi; Khumalo, 2025).

Complementarily, the integration of AI and computer vision has promoted significant advances in modernizing phytopathology by automating detection processes, reducing operational costs, and decreasing reliance on exclusively expert-based field assessments. The development of more robust algorithms strengthens precision agriculture, enabling earlier diagnostics and more assertive management strategies (Nyawose, Maswanganyi & Khumalo, 2025).

However, it is essential to recognize that the choice of AI techniques must consider not only performance metrics, such as accuracy, but also aspects related to interpretability, computational cost, and implementation feasibility in sustainable agricultural systems. In this sense, selecting algorithms for field applications must balance technical efficiency with practical applicability, as limitations such as low connectivity in rural areas and high investment costs demand solutions capable of operating autonomously or under restricted digital infrastructure (Marella *et al.*, 2025).

DATABASES AND SENSING APPLIED TO PLANT DISEASE DETECTION: RGB, MULTISPECTRAL, AND HYPERSPECTRAL IMAGERY, AND UNMANNED AERIAL VEHICLES (UAVS)

The performance of Artificial Intelligence models applied to phytopathology is directly conditioned by the quality, diversity, and representativeness of the datasets used in the training and validation stages. Well-structured databases enable AI systems to learn visual and physiological patterns associated with plant diseases, reducing classification errors and increasing the reliability of automated diagnostics (González-Rodríguez *et al.*, 2024). However, it is observed that most currently available datasets are composed of images obtained under controlled conditions, which compromises the generalization capability of the models when applied in real-world agricultural environments characterized by high spatial and environmental heterogeneity (Mohanty *et al.*, 2016; Appeltans *et al.*, 2022).

Within this context, RGB imagery represents the most widely used data type in plant disease detection studies via AI, primarily due to the ease of acquisition using conventional cameras and

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mobile devices (Li *et al.*, 2025). This type of imagery is particularly effective for identifying evident visual symptoms, such as leaf spots, chlorosis, and necrosis, allowing for high accuracy levels in models based on Convolutional Neural Networks. However, the direct reliance on the visual manifestation of symptoms limits the early detection of diseases, especially in the initial stages of infection or in situations where abiotic stresses mask pathological signs (Mehedi *et al.*, 2024).

As an alternative to these limitations, multispectral sensing has gained increasing relevance in AI-assisted phytopathology, as it allows for the capture of information beyond the visible spectrum, including near-infrared (NIR) bands, which are sensitive to physiological changes related to water status and plant cellular integrity. These data enable the identification of infections before the visual expression of symptoms, considering that plant diseases alter reflectance patterns associated with photosynthesis and chlorophyll content. Integrating multispectral information with machine learning and deep learning algorithms substantially expands AI's potential for early diagnosis and phytosanitary monitoring (Kim & Lee, 2020).

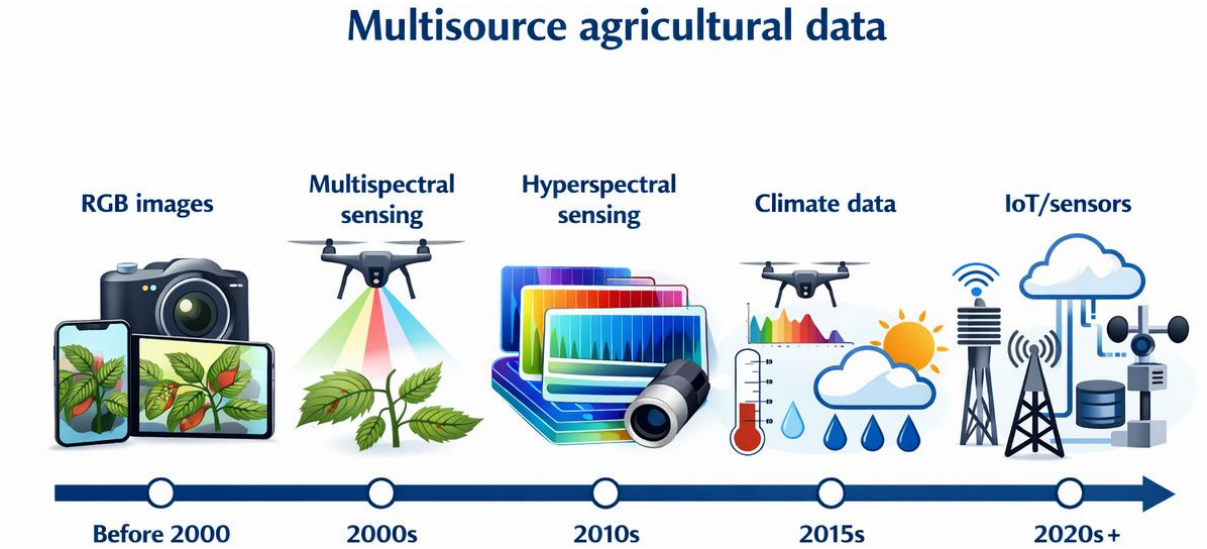
Advancing in the same direction, hyperspectral sensing represents an evolution over multispectral approaches by providing hundreds of continuous spectral bands that allow for the detailed identification of specific spectral signatures associated with different pathogens. Diseases of fungal, bacterial, and viral origin induce distinct metabolic changes in plants, which can be detected by hyperspectral sensors even in asymptomatic stages. Despite its high potential for predictive applications in phytopathology, the use of this technology still faces significant challenges, including high sensor costs, the large volume of data generated (data dimensionality), and the high computational complexity required for analysis by AI models (Kim & Lee, 2020; Barreto *et al.*, 2023).

Complementarily, the incorporation of Unmanned Aerial Vehicles (UAVs) has significantly expanded the spatial scale of AI applications in plant disease detection and monitoring (Albiero *et al.*, 2022). UAVs equipped with RGB, multispectral, or hyperspectral sensors enable rapid and repetitive data acquisition over extensive agricultural areas, facilitating the spatial mapping of disease incidence and severity. When integrated with AI algorithms, these systems become strategic tools for precision agriculture, allowing for site-specific interventions and contributing to the reduction of chemical pesticide use (Emmi *et al.*, 2014). The main data sources used in AI systems applied to the detection and monitoring of plant diseases are outlined in Figure 2.

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Figure 2. Representative scheme of sensing modalities applied to digital phytopathology: integration of orbital, suborbital (UAVs), and terrestrial sensors for multispectral phytosanitary monitoring



Despite these technological advancements, the construction of robust and broadly applicable datasets for phytopathology still faces substantial limitations. The scarcity of standardized datasets, properly labeled by experts and representative of the variability observed under real-world field conditions, constitutes one of the primary obstacles to the advancement of Artificial Intelligence in this field. Furthermore, factors such as lighting variations, acquisition angles, background complexity, and interference from abiotic stresses compromise the reliability of models when extrapolated to uncontrolled environments. This reinforces the need for integrated strategies for data collection, standardization, and validation under actual cultivation conditions (Chen *et al.*, 2024).

PERFORMANCE METRICS AND GENERALIZATION CHALLENGES IN ARTIFICIAL INTELLIGENCE MODELS APPLIED TO PHYTOPATHOLOGY

The evaluation of Artificial Intelligence (AI) model performance in plant disease detection and classification is a central element in ensuring both the reliability of results and the feasibility of their practical application. In this context, metrics such as accuracy, precision, sensitivity (recall), specificity, F1-score, and the Area Under the ROC Curve (AUC) are widely employed to quantify the models' ability to correctly discriminate between healthy and infected plants (Dayang & Meli, 2021). Although accuracy is frequently reported as the primary metric in disease detection studies, its use in isolation can mask relevant limitations, especially in imbalanced datasets, where the predominance of one class tends to artificially inflate performance results (Teghipco *et al.*, 2024; Nyawose; Maswanganyi; Khumalo, 2025).

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Given these limitations, metrics based on sensitivity and specificity assume a particularly relevant role in phytopathological applications, as classification errors can lead to significant agronomic consequences. Low sensitivity, associated with the occurrence of false negatives, can delay phytosanitary interventions and favor pathogen dissemination in the field. Conversely, low specificity, characterized by false positives, can result in the unnecessary application of pesticides. Thus, the appropriate selection of evaluation metrics must align with the specific objective of the AI system, whether it be early diagnosis, continuous monitoring, or decision support in Integrated Disease Management (IDM) (González-Rodríguez *et al.*, 2024).

Beyond classical classification metrics, more recent approaches have emphasized the importance of evaluating model robustness and stability, analyzing performance under varying lighting conditions, capture angles, phenological stages, and levels of disease severity (Li & Chao, 2021). Several studies indicate that models showing high performance on experimental datasets often suffer significant degradation when applied in real-world field scenarios, highlighting the recurring occurrence of overfitting to training data (Appeltans *et al.*, 2022; Bohnenkamp *et al.*, 2021).

This behavior is directly related to the challenge of generalization, widely recognized as one of the main obstacles to the effective adoption of AI in phytopathology. Models trained on a specific crop, variety, or geographical region tend to show reduced performance when transferred to other production contexts due to plant genetic variability, pathogen diversity, and the influence of environmental factors. This limitation reinforces the need for more diverse datasets that are representative of actual agricultural production conditions, capable of sustaining more robust and generalizable models (Kim & Lee, 2020).

Additionally, model generalization is compromised by the interference of abiotic stresses, such as nutritional deficiencies, drought, or mechanical damage, which can generate visual symptoms similar to those caused by biotic diseases. Many AI systems still struggle to discriminate between biotic and abiotic symptoms, resulting in misclassifications and reduced model reliability in complex agricultural environments. This challenge highlights the importance of integrating multi-source data, including climatic and spectral information, as a strategy to enhance the discriminative capacity of algorithms (Zarco-Tejada *et al.*, 2021).

Finally, studies focused on agricultural sustainability emphasize that AI model performance evaluation must be conducted in an integrated manner with operational criteria, such as computational cost, processing time, and the feasibility of implementation in embedded systems. As noted by Li *et al.* (2025), models that achieve high precision levels but demand extensive computational capacity may become unviable for real-time field applications, especially in regions with limited technological infrastructure. Thus, the performance evaluation of AI systems in phytopathology must transcend purely statistical metrics, incorporating analyses of generalization, robustness, and practical

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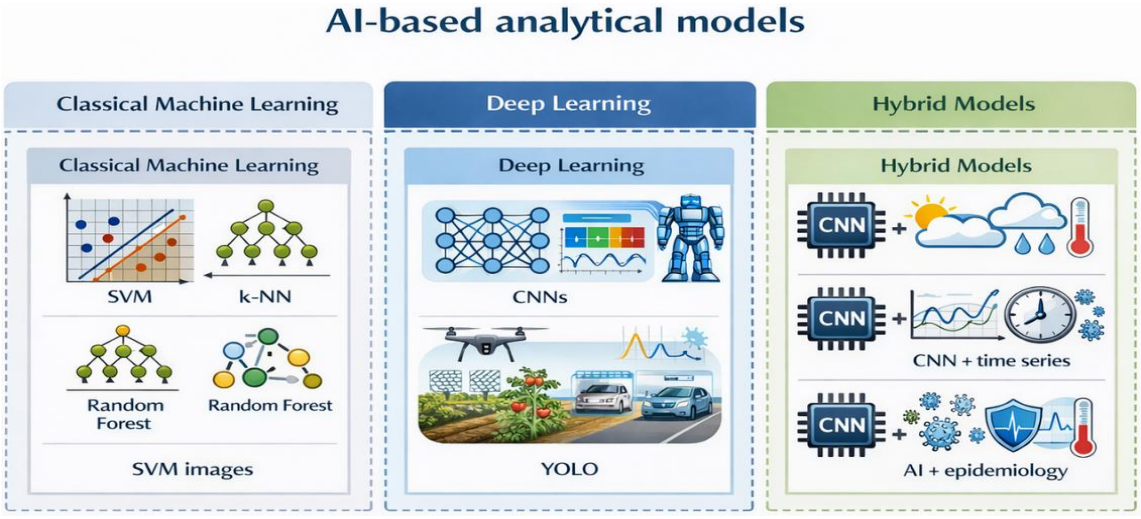
applicability to favor technically efficient and operationally sustainable solutions (Ampatzidis, Bellis & Luvisi, 2017).

INTEGRATION OF ARTIFICIAL INTELLIGENCE WITH TEMPORAL PLANT DISEASE FORECASTING AND CLIMATIC FACTORS

The temporal dynamics of plant diseases are strongly conditioned by environmental factors, particularly climatic variables such as temperature, precipitation, relative humidity, and solar radiation, which modulate both pathogen development and host plant susceptibility. Historically, the forecasting of phytopathological outbreaks relied on epidemiological models based on empirical rules and degree-day accumulation. Although widely used, these models present significant limitations when applied to complex and non-linear agricultural systems. In this context, the integration of artificial intelligence with climatic data emerges as a promising approach to enhance the temporal forecasting of plant disease occurrence and severity (González-Rodríguez *et al.*, 2024; Lucas *et al.*, 2015).

Driven by the need for greater predictive capacity, supervised machine learning models have been extensively employed to associate time series of climatic variables with disease incidence across various crops. Algorithms such as multiple regression, Random Forest, and Gradient Boosting demonstrate a high capacity to identify complex relationships between environmental factors and disease progression, outperforming traditional linear models. These methods enable the development of early warning systems (EWS), capable of identifying periods of higher epidemiological risk and supporting risk-based phytosanitary management decisions (Nyawose, Maswanganyi & Khumalo, 2025). The evolution of these methods is presented in Figure 3.

Figure 3. Classification and structuring of AI-based analytical models: from classical machine learning and convolutional neural networks to the integration of hybrid models for epidemiological analysis



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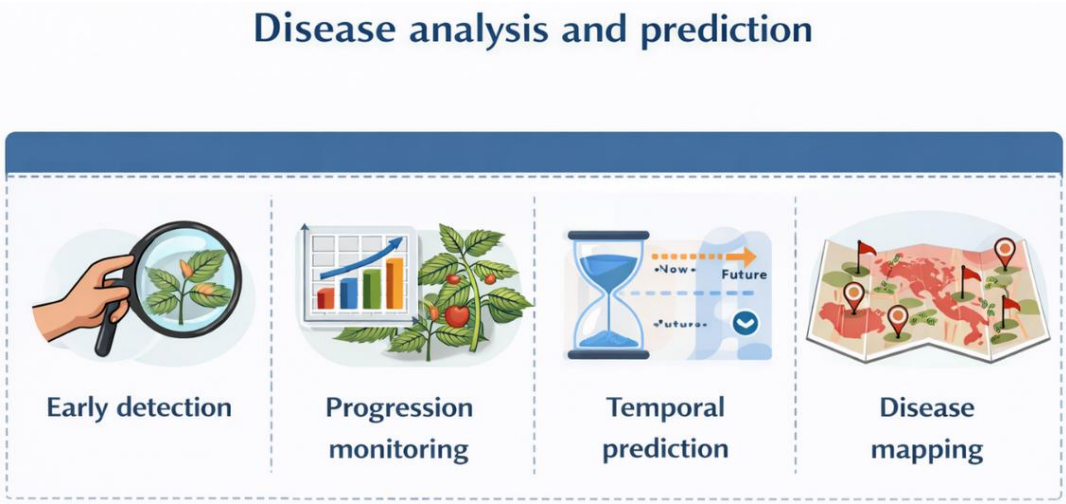
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With the evolution of deep learning, neural architectures specifically designed for temporal analysis—such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models—have been incorporated into predictive phytopathology (Otero *et al.*, 2022). These models are particularly efficient at capturing temporal dependencies between climatic variables and disease evolution, allowing for more accurate forecastings of both severity and the timing of outbreaks. Furthermore, the ability to integrate multiple environmental variables over time makes these architectures especially relevant in agricultural scenarios characterized by high climatic variability (González-Rodríguez *et al.*, 2024).

Beyond isolated temporal analysis, recent studies emphasize the importance of integrating temporal information with spatial data derived from remote sensing and Unmanned Aerial Vehicles (UAVs). The fusion of multi-temporal imagery with meteorological variables enables continuous monitoring of the spatial progression of diseases, facilitating the early identification of initial infection foci and the evaluation of the effectiveness of control strategies adopted throughout the crop cycle.

This integrated approach reinforces the role of Artificial Intelligence as a core component of Decision Support Systems (DSS) aimed at Integrated Disease Management (IDM) (Kim & Lee, 2020). The convergence of these technologies allows digital phytopathology to operate across different analytical dimensions, ranging from initial diagnostic identification and field severity monitoring to the anticipation of outbreaks via predictive models and the mapping of risk in epidemiological maps (Figure 4).

Figure 4. Dimensions of analysis and forecasting in digital phytopathology: integration between early detection, disease progression monitoring, temporal risk modeling (temporal forecasting), and georeferenced incidence mapping (disease mapping)



Overall, the integration of Artificial Intelligence with temporal disease forecasting and climatic factors represents a significant conceptual advancement in modern phytopathology. It enables the

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transition from essentially reactive strategies to preventive and predictive approaches in phytosanitary management. AI-based systems have high potential to reduce yield losses, optimize input usage, and promote agricultural systems that are more resilient to climate change. However, the effectiveness of these approaches depends on the development of models built upon representative datasets and properly validated under real-world field conditions to ensure their practical applicability and long-term sustainability (Brynjolfsson & Mitchell, 2017; Hassan & Maji, 2022).

CURRENT LIMITATIONS AND CHALLENGES FOR THE PRACTICAL APPLICATION OF ARTIFICIAL INTELLIGENCE IN PHYTOPATHOLOGY

Despite the significant progress observed over the last decade, the practical application of Artificial Intelligence (AI) systems in phytopathology still faces relevant limitations, particularly regarding model robustness when subjected to real-world field conditions. A large portion of algorithms is developed and validated in controlled environments using images with homogeneous backgrounds and ideal lighting conditions—a scenario that does not adequately represent the complexity of commercial agricultural systems. Consequently, the performance of these models tends to decrease significantly when exposed to environments characterized by high environmental variability (Pethybridge & Nelson, 2015).

This discrepancy between experimental environments and actual cultivation conditions is directly associated with the intrinsic heterogeneity of the field, which constitutes one of the primary challenges for the generalization of AI models. Factors such as lighting variations, presence of dust, leaf overlap, mechanical damage, and weed interference can compromise image quality and induce errors in classification algorithms. These elements introduce noise into the data and make it difficult to distinguish between symptoms caused by pathogens and physiological responses to abiotic stresses, substantially reducing the reliability of automated diagnostics in complex agricultural environments (Li & Chao, 2021; Vishnoi *et al.*, 2022).

In addition to these environmental challenges, the scarcity of large, diverse, and properly expert-labeled datasets represents another critical limitation for the advancement of AI in phytopathology. As highlighted by Kim *et al.* (2020), most available datasets cover a restricted number of crops, pathogens, and environmental conditions, which limits the models' ability to learn truly generalizable patterns. Furthermore, the labeling process requires a high level of technical expertise, making the construction of robust databases a costly, time-consuming activity dependent on the availability of qualified specialists (Nyawose; Maswanganyi; Khumalo, 2025; Kim & Lee, 2020).

From an operational standpoint, high computational costs and the need for adequate technological infrastructure pose additional barriers to AI implementation in agricultural systems. High-complexity models require high-performance hardware for both training and inference, which may render their adoption unfeasible for small and medium-sized farms, especially in developing countries.

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This reality reinforces the demand for more computationally efficient solutions, capable of operating with lower resource consumption and adapted to local agricultural production conditions (Kim & Lee, 2020).

Additionally, the lack of methodological standardization in the evaluation of AI models makes it difficult to compare studies and compromises the independent validation of results. Differences in data acquisition protocols, performance metrics, and validation strategies contribute to the fragmentation of scientific knowledge and delay the transfer of developed technologies to commercial applications. Overcoming these limitations is essential to consolidate Artificial Intelligence as an effective, reliable, and broadly applicable tool in Integrated Disease Management (IDM) (Mahlein, 2016).

FUTURE DIRECTIONS: EDGE COMPUTING, IOT, AND DISTRIBUTED SENSORS IN AI-BASED PHYTOPATHOLOGY

The incorporation of edge computing into AI-based phytopathological diagnostic systems stands out as one of the most promising branches of contemporary digital agriculture. In contrast to architectures based exclusively on cloud computing, edge processing enables data analysis directly at the point of acquisition, such as in field-installed sensors or imaging systems embedded in Unmanned Aerial Vehicles (UAVs). As discussed by Shi *et al.* (2016), this strategy significantly reduces latency, bandwidth consumption, and reliance on continuous connectivity, favoring near-real-time phytopathological diagnostics and swifter decision-making in plant disease management.

Complementarily, the Internet of Things (IoT) holds high potential to redefine phytosanitary monitoring by allowing for the continuous, automated, and integrated acquisition of environmental, physiological, and pathological variables. Sensors designed to measure temperature, relative humidity, leaf wetness, solar radiation, and gas concentration can be interconnected with intelligent platforms, providing inputs for predictive disease occurrence models. According to Kamilaris *et al.* (2018), the integration of IoT with machine learning algorithms substantially expands the capacity to anticipate epidemic outbreaks, enabling more efficient preventive interventions aligned with the principles of agricultural sustainability.

In this context, distributed sensors play a strategic role in the consolidation of intelligent phytopathological systems, especially in extensive agricultural environments with high spatial heterogeneity. Wireless Sensor Networks (WSN) allow for obtaining microclimatic and spectral data in a spatially explicit manner, providing detailed information on intra-plot variability. According to Duo *et al.* (2020), this approach contributes to enhancing the spatial resolution of AI-based models, favoring localized diagnostics and the development of precision management strategies directed at plant disease control.

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A conceptual evolution of these systems emerges with the incorporation of bio-hybrid plants as active sensing elements, expanding the possibilities for integration between biological and technological systems. As proposed by Hamann *et al.* (2015), bio-hybrid plants can act as highly sensitive biosensors, since the plant itself functions as a primary biological sensor capable of responding to multiple environmental stimuli. Associated technological sensors capture environmental, electrophysiological, photosynthetic, and fluid-dynamic responses, converting them into digitized and structured information, resulting in the formation of advanced phytosensing systems applicable to phytopathological diagnosis and monitoring.

Finally, the consolidation and large-scale application of these technologies require multidisciplinary efforts focused on protocol standardization, interoperability between devices, and validation under real-world field conditions. The effective adoption of edge computing, IoT, distributed sensors, and phytosensing systems in phytopathology does not depend exclusively on the technical performance of AI models, but also on their integration with agronomic knowledge, plant ecophysiology, and the operational particularities of production systems.

FINAL CONSIDERATIONS

The application of Artificial Intelligence (AI) in phytopathology has driven significant advancements in the detection, monitoring, and forecasting of plant diseases, establishing itself as a strategic tool for modern agriculture. Throughout this review, it has been demonstrated that the evolution of AI techniques—from classical machine learning methods to advanced deep learning architectures such as CNNs, Transformers, and hybrid models—has substantially expanded the capacity for automated diagnosis and the analysis of complex patterns associated with pathogen–host–environment interactions.

It was observed that the combined use of diverse data sources, including RGB, multispectral, and hyperspectral imagery, as well as information derived from UAVs and field sensors, has been fundamental in enhancing model accuracy and robustness. However, challenges persist regarding dataset standardization, the variability of field conditions, and model generalization across different crops, regions, and phenological stages, which limits the direct transfer of experimental results to large-scale practical applications.

The integration of AI with temporal forecasting models and climatic variables has proven particularly promising, enabling more dynamic and preventive approaches in phytosanitary management. Nonetheless, limitations related to model interpretability, the need for agronomic validation, and adaptation to actual production conditions reinforce the importance of interdisciplinary approaches that combine data science, phytopathology, and agronomic expertise.

Furthermore, the present review highlights that important scientific and operational gaps still restrict the consolidation of AI-based systems under real-world agricultural conditions. Among the main

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limitations identified are the lack of methodological standardization in agricultural dataset construction, the limited representativeness of databases in relation to the high edaphoclimatic and phytosanitary variability of production systems, and the reduced capacity of models to generalize and transfer across different crops, geographical regions, and epidemiological scenarios. In addition, the necessity for more robust agronomic validation under field conditions remains essential to ensure the reliability and practical applicability of intelligent phytosanitary monitoring systems.

Although deep learning architectures have demonstrated high forecasting performance, challenges associated with model interpretability still persist, limiting the biological understanding of the decision-making processes employed by AI algorithms. In this context, approaches based on Explainable Artificial Intelligence (XAI), mitigation of bias in agricultural datasets, and interoperable integration among remote, proximal, and embedded sensing platforms emerge as strategic priorities for future investigations. Likewise, emerging technologies such as Vision Transformers, foundation models, and federated learning applied to distributed agricultural systems show considerable potential to expand the robustness, scalability, and adaptability of digital phytopathology. However, the consolidation of these technologies will depend not only on computational advances, but also on the establishment of guidelines related to agricultural data governance, digital sustainability, information security, and the economic feasibility of technological adoption by small and medium-sized producers.

Finally, future directions point toward the consolidation of intelligent systems based on edge computing, the Internet of Things (IoT), and distributed sensors, capable of operating autonomously, in real-time, and with greater energy efficiency. These advancements are poised to facilitate a more predictive, precise, and sustainable phytopathology, contributing to the reduction of indiscriminate pesticide use and the strengthening of food security. Thus, Artificial Intelligence emerges not merely as a technological tool, but as a core element in the transformation of plant disease management systems facing the challenges of 21st-century agriculture.

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