



Plant Disease Pathology: Causes, Machine Learning-based Detection and Sustainable Management Strategies

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ABSTRACT

Background: Plant diseases are a major challenge for global food production. They lead to significant reductions in crop yield and quality. Fungi, bacteria, viruses and nematodes are common pathogens that attack plants. These diseases not only affect food security but also cause economic losses worldwide. Estimates show that 20-30% of global crop yields are lost annually due to plant diseases. Early detection is necessary to minimize losses and protect crops. Traditional detection methods rely on field observation and laboratory tests. These techniques are time-consuming, labor-intensive and may not be practical for large-scale monitoring. Modern tools, including imaging technologies and machine learning, are emerging as effective solutions. They offer rapid, accurate detection and classification of plant diseases.

Methods: This paper reviews plant disease detection techniques with a focus on classification systems and diagnostic tools. The classification is based on disease incidence, mode of spread, symptoms, host parts affected and causative agents. A literature search was performed using databases such as Scopus, Web of Science and Google Scholar. Keywords included "plant disease detection," "machine learning," "AI in agriculture," and "disease management." Studies from 2005 to 2024 were considered. Priority was given to research discussing image-based diagnosis, hyperspectral imaging and machine learning models. Relevant articles were analyzed for methods, performance and limitations.

Result: Machine learning-based models show strong potential for disease detection. Convolutional neural networks (CNNs) are widely used for image classification tasks. Hyperspectral imaging and sensor-based systems improve accuracy. However, limitations exist. Models struggle with dataset imbalance, varying environmental conditions and real-field application. More diverse datasets and field validation are needed. Explainable AI models are also lacking.

Key words: Artificial intelligence, Crop health monitoring, Disease classification, Machine learning, Plant disease detection.

INTRODUCTION

Plants are essential for the existence of life on Earth. They serve as the primary source of food for humans, animals and billions of microorganisms that inhabit the environment. Despite humans' ability to domesticate plants and animals for their benefit, competitive microorganisms persist in resisting these efforts and continue to consume significant portions of resources intended for human use (Agrios, 2005; Savary *et al.*, 2019). In this context, it has become increasingly necessary to combat competing microorganisms and other biotic or abiotic agents that lead to reduced plant performance and yield (Fletcher *et al.*, 2006). The attack of these microorganisms on plants not only alters the appearance of crops but also reduces their productivity and this phenomenon is commonly referred to as an ailment. Plant diseases have long been recognized as major obstacles to achieve rapid advancements in global food production (Dean *et al.*, 2012). A plant can be considered healthy only if it continues to perform its physiological functions and yields the expected harvest based on its genetic potential. The key physiological functions of a healthy, thriving plant include.

- Normal cell differentiation, division and growth.
- Absorption of water and nutrients from the soil.
- Photosynthesis to convert sunlight into energy-rich food.
- Transport of water and nutrients through the phloem and xylem.

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- Metabolism of synthetic materials.
- Successful reproduction and propagation.

In diseased plants, some or all of these functions are disrupted. The extent of disease impact depends on which

cells or tissues the pathogen initially targets. For example, decaying root tissues result in impaired water and mineral absorption; damage to vascular tissues restricts the transport of water and photosynthates, while attacks on leaf tissues disrupt photosynthesis, leading to carbohydrate deficiency, which hampers other critical physiological processes (Velásquez *et al.*, 2018). Illness, therefore, can be described as a malfunctioning physiological state caused by constant irritation from a pathogen. According to definitions by the American Phytopathological Society and the British Mycological Society, plant disease is a continuous disturbance of normal plant functions, resulting in symptoms and physiological distress. This persistent disturbance leads to dysfunction in the tightly regulated sequence of physiological activities, ultimately disrupting the plant's energy balance and metabolic harmony (Agrios, 2005). The disease process, caused by pathogenic organisms or environmental stressors, manifests through several interconnected mechanisms.

- Utilization of host cell components by pathogens.
- Disruption of metabolism or induction of cell death through secretion of toxins, enzymes, or growth regulators.
- Nutrient depletion, causing weakened plant tissues.
- Interruption of resource remobilization, including carbohydrates, minerals and water (Savary *et al.*, 2019).

The objectives of plant pathology, a scientific discipline addressing plant health, are as follows:

- To study the non-living, living and environmental factors causing plant diseases.
- To understand the mechanisms of disease development and pathogen-host interactions.
- To analyze plant-pathogen relationships at cellular, molecular and ecological levels.
- To develop disease management strategies aimed at reducing crop losses and improving productivity (Fletcher *et al.*, 2006).

Plant diseases are a major challenge to global food security. They cause significant reductions in crop yield and quality. Pathogens such as fungi, bacteria, viruses and nematodes attack various plants. These infections result in heavy economic losses worldwide. Estimates suggest that plant diseases cause 20-30% of global crop losses each year (Savary *et al.*, 2019). Early diagnosis and proper management are essential to reduce these losses. Rapid detection helps in timely control, preventing large-scale outbreaks. Recent advancements in plant pathology have introduced modern tools for disease detection and management (Buja *et al.*, 2021; Kamilaris and Prenafeta-Boldú, 2018; Mahlein, 2015). These tools include molecular diagnostics, imaging technologies and data-driven solutions (Zhao *et al.*, 2014; Liu *et al.*, 2023; Ciotti *et al.*, 2024). Together, they improve crop health monitoring and support sustainable agriculture.

In recent years, plant disease detection and management have been increasingly supported by advancements in artificial intelligence and machine learning technologies. These tools are being used to

enhance early disease detection, improve diagnostics and automate large-scale monitoring in agricultural fields (Chauhan *et al.*, 2024; Cho, 2024; Hai and Duong, 2024; Semara *et al.*, 2024; Maltare *et al.*, 2023; AlZubi, 2023). The application of deep learning-based image analysis systems, hyperspectral imaging and sensor-based precision agriculture tools have shown great promise in mitigating plant disease outbreaks and reducing economic losses (Wang *et al.*, 2024). Such technologies are becoming vital in strengthening food security, enabling rapid response strategies and ensuring sustainable crop production in the face of climate change and emerging plant pathogens (Velásquez *et al.*, 2018; Savary *et al.*, 2019).

This paper reviews recent advances in plant disease diagnosis and management, with a particular focus on the growing role of machine learning technologies.

MATERIALS AND METHODS

Cataloging of plant diseases

Plant diseases can be classified based on various factors, including incidence, mode of spread, host specificity, symptoms and the nature of the causative agent. Proper categorization aids in understanding disease etiology, tracking disease progression, assessing crop damage and implementing suitable control measures (Agrios, 2005).

Classification based on frequency of incidence

Plant diseases may be categorized according to their frequency of occurrence.

- Infectious diseases are those that spread quickly through pathogens, such as, the late blight of potatoes caused by *Phytophthora infestans* spreads quickly, especially in wet and humid conditions.
- Contagious diseases develop gradually but are also caused by communicable pathogens. For example- Powdery mildew on cucurbits caused by *Podosphaera xanthii* slowly spreads from infected to healthy plants, especially under warm and dry conditions.
- Endemic diseases are those that recur every year within a particular geographical region, although the severity may vary. For example, Grape fruit rot caused by *Greeneria uvicola* is an endemic disease in India, consistently occurring every season with differing intensities (Vitale, 2023).
- Epidemic diseases, also referred to as *epiphytotic*s, occur periodically, often spreading rapidly across large areas. The occurrence of such diseases is heavily influenced by environmental conditions that favor pathogen development, for example, rice blast disease caused by *Magnaporthe oryzae* often occurs in epidemic proportions during warm and wet conditions, resulting in significant crop losses (Agrios, 2005).

Classification based on the medium of spread

Plant diseases can also be classified based on the medium through which the pathogens are transmitted. The major categories include:

Seed-borne diseases: Transmitted through infected seeds, leading to early-stage infections in seedlings and often causing significant crop losses.

Soil-borne diseases: These persist in the soil and infect plants through roots or lower stems, making them challenging to manage due to their long survival in the soil.

Air-borne (wind-borne) diseases: Spread through wind-dispersed spores or pathogens, enabling rapid and wide dissemination, often resulting in epidemics.

Water-borne diseases: Transmitted through irrigation water, rain splash, or surface runoff, which can carry pathogens from infected fields to healthy plants. Understanding these transmission channels is crucial for developing targeted disease prevention, monitoring and control strategies (Gai and Wang, 2024).

Classification based on the host part affected

- **Stem diseases:** These diseases primarily affect the stem, weakening the structural support of the plant, often leading to lodging (falling over) or breakage. Symptoms may include lesions, cankers, or rotting of the stem. For example: Stem rust of wheat is caused by *Puccinia graminis*, which produces reddish-brown pustules on the stem and disrupts nutrient flow. The black shank of tobacco is caused by *Phytophthora nicotianae*, leading to blackened, rotting lesions at the base of the stem.

- **Foliage diseases:** Foliage diseases affect the leaves of the plant, impacting photosynthesis and overall plant vitality. Common symptoms include spots, blights, rust and powdery coatings. For example-Early blight of tomato caused by *Alternaria solani*, which results in characteristic concentric ring spots on leaves, leading to defoliation. Powdery mildew in cucurbits caused by *Podosphaera xanthii*, presenting as white powdery growth on leaf surfaces.

- **Vascular diseases:** These diseases attack the vascular system (xylem or phloem), obstructing the transport of water and nutrients throughout the plant. As a result, symptoms like wilting, yellowing and stunted growth appear even when soil moisture is adequate. For example- The fusarium wilt of banana is caused by *Fusarium oxysporum* f. sp. *cubense*, which blocks the xylem vessels, leading to yellowing and wilting of leaves. Verticillium wilt of cotton is caused by *Verticillium dahliae*, where vascular blockage results in partial or complete plant wilt.

- **Root diseases:** These diseases affect the root system, compromising the plant's ability to absorb water and nutrients and often lead to poor growth, wilting and plant death. Symptoms include root decay, root rot and discoloration. Examples: Root rot of beans caused by *Rhizoctonia solani*, resulting in soft, decayed and discolored roots. Clubroot of crucifers caused by *Plasmodiophora brassicae*, where roots become swollen and deformed, severely stunting plant growth (Vitale, 2023).

Classification based on host specificity

Plant diseases can also be classified according to the type of host plant they affect. Although this method of

classification is based more on convenience than on strict scientific principles. It helps in grouping diseases relevant to specific crop categories. Vegetable diseases are those that impact vegetable crops, often reducing yield and quality. An example is downy mildew of cucumber, caused by *Pseudoperonospora cubensis*, which severely damages the foliage, affecting photosynthesis and fruit development. Fruit crop diseases affect fruit-bearing plants and trees; for instance, apple scab, caused by *Venturia inaequalis*, leads to dark, scabby lesions on fruits and leaves, reducing market value. Cereal diseases are common in grains, such as rice blast disease, caused by *Magnaporthe oryzae*, which can lead to significant crop loss in rice fields worldwide. Timber plant diseases are those that affect trees grown for wood; for example, heart rot in teak trees, caused by *Phellinus* spp., leads to internal decay of wood, making it unsuitable for timber. Ornamental plant diseases affect plants grown for decorative purposes; an example is leaf spot disease in roses, caused by *Diplocarpon rosae*, resulting in unsightly black spots on leaves. Lastly, shade tree diseases affect large trees often used for landscaping and environmental protection. An example is Dutch elm disease, caused by the fungus *Ophiostoma ulmi*, which has devastated elm populations in many countries. This classification helps farmers, gardeners and forestry professionals focus disease management practices on specific plant categories (Sharma and Sharma, 2023).

Classification based on symptoms

Another practical method of classification is based on the visible symptoms shown by infected plants. These include necrotic diseases, which result in the death of plant tissues; atrophic diseases, which cause stunting and underdevelopment of plant parts and hypertrophic diseases, which are marked by abnormal or excessive growth. Common disease names based on symptoms include blight, rust, rot, smut, mildew and canker. Symptom-based classification plays an important role in field diagnosis and helps guide immediate disease management decisions (Agrios, 2005).

Classification based on causative agents

Plant diseases can be broadly classified into two main categories based on their causative agents: parasitic and non-parasitic (Schumann and D'Arcy, 2006). Fig 1 depicts the primary and secondary disease cycle.

Parasitic agents

Parasitic agents are living organisms that live on or inside the plant and cause damage. These organisms either absorb nutrients, block physiological processes, or destroy plant tissues. The severity of damage varies depending on the type of parasite and the plant's resistance. Some parasites kill the host quickly, while others weaken the plant over time. The major parasitic agents include:

Bacteria: These are microscopic single-celled organisms. They infect plant tissues and spread through water, wind,

insects, or contaminated tools. Example: *Xanthomonas oryzae* causes bacterial leaf blight in rice. *Erwinia amylovora* causes fire blight in apples and pears.

Fungi: These are spore-producing organisms that thrive in warm and humid conditions. Fungal infections can lead to root rot, wilting and leaf spots. Example: *Fusarium oxysporum* causes wilt in tomato. *Puccinia graminis* causes stem rust in wheat.

Slime molds: Slime molds grow on plant surfaces and appear as slimy, jelly-like masses. They are usually harmless but can reduce photosynthesis if they cover large leaf areas. Example: *Physarum* species form unsightly masses on grass and leaves in moist conditions.

Parasitic angiosperms (Flowering plant parasites): These are plants that attach themselves to other plants and absorb nutrients from them. Example: *Cuscuta* (dodder) is a leafless, twining parasitic plant that attacks crops like alfalfa and clover.

Viruses: These are tiny infectious particles that depend on the host's cells to replicate. They are often spread by insect vectors. Example: Tobacco mosaic virus (TMV) infects tobacco and tomato plants, causing mosaic-like patterns on leaves. Banana bunchy top virus causes stunted, clustered leaves in banana plants.

Algae: Algae are green, photosynthetic organisms that can sometimes infect plants, particularly in moist and humid regions. Example: *Cephaleuros virescens* causes red rust in tea and mango.

Insects: Insects damage plants directly by feeding on them and indirectly by transmitting diseases. Example: Aphids feed on sap and transmit plant viruses. Whiteflies spread yellow vein mosaic disease in okra.

Mites: Mites are small arthropods that feed on plant cells. Their feeding causes leaf curling, yellowing and poor growth. Example: Red spider mites attack cotton, beans and vegetables.

Nematodes: Nematodes are microscopic worms that attack plant roots, causing swelling or galls and reducing nutrient uptake. Example: Root-knot nematodes (*Meloidogyne* spp.) attack tomato, brinjal and other vegetables.

Non-parasitic agents

Non-parasitic agents are environmental or chemical factors that cause physiological disorders in plants. These factors are not caused by living organisms but by unfavorable conditions that disrupt the plant's normal functions. Major non-parasitic agents include:

Nutritional deficiencies: When plants do not receive enough essential nutrients, they show symptoms like yellowing, stunted growth and poor fruiting. Examples: Iron deficiency causes interveinal chlorosis in cabbage leaves. Boron deficiency leads to hollow heart in cauliflower. Potassium deficiency causes scorching of leaf edges.

Imbalance in soil moisture: Both excessive moisture and drought stress can harm plants. Examples: Overwatering can cause root rot in tomato and chili plants. Water scarcity leads to wilting and die-back in herbaceous plants. Blossom-end rot in tomato is a classic example caused by irregular watering and calcium deficiency. Verticillium wilt of tomato is a significant plant disease caused by the soil-borne fungus *Verticillium dahliae* or *Verticillium albo-atrum* (Fig 2).

Light intensity asymmetry: Plants need balanced light for proper photosynthesis. Too little or too much light can affect growth. Examples: Low light leads to weak, elongated stems (etiolation) in seedlings. Intense sunlight can cause sunscald on tomato fruits.

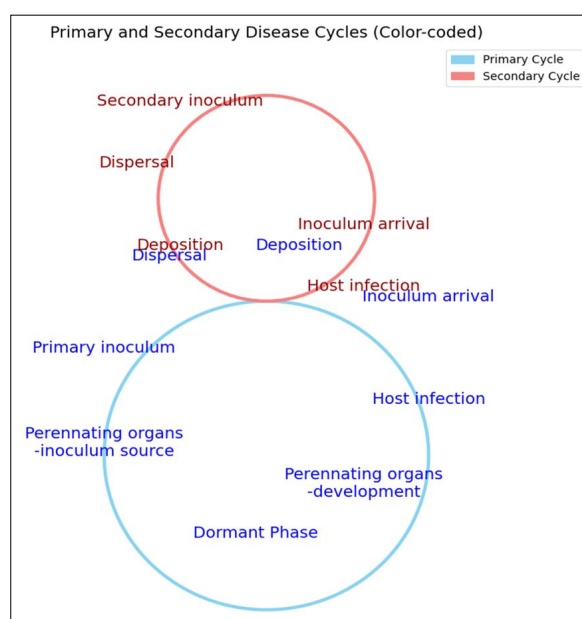


Fig 1: Primary and secondary disease cycle.

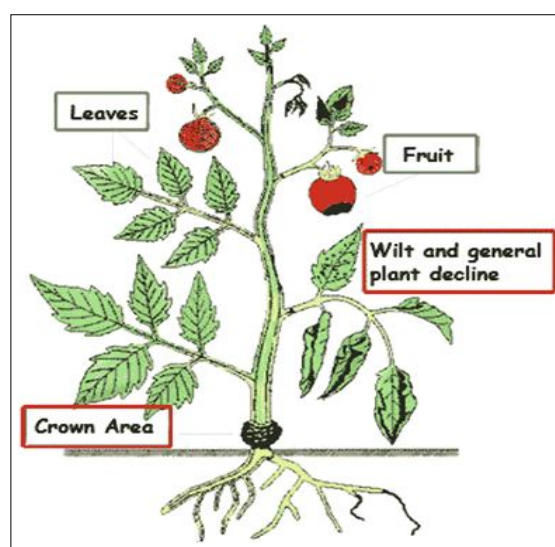


Fig 2: Verticillium wilt of tomato.

Temperature extremes: Plants have specific temperature ranges for optimum growth. Deviations cause stress and disorders. Examples: Frost damage leads to leaf burn in potatoes and peas. High temperatures cause flower drops in tomatoes and chilies.

Air pollutants (Gases, smoke): Polluted air with sulfur dioxide, ozone, or smoke damages leaf tissues. Examples: Ozone injury causes flecking and bronzing of tobacco leaves. Sulfur dioxide pollution leads to leaf spotting in sensitive plants.

Chemical misuse: Improper use of fertilizers and pesticides can harm plants. Examples: Excess nitrogen causes lush, weak growth and makes plants more prone to diseases. Herbicide drift can cause leaf curling and burning in non-target crops.

RESULTS AND DISCUSSION

Purpose of disease classification

Classifying plant diseases plays a vital role in plant health management. It helps in understanding the exact cause of the disease, whether it is due to fungi, bacteria, viruses, nematodes, or environmental factors. For instance, determining whether tomato wilting is caused by *Fusarium* fungus, bacterial infection, or nematodes is crucial for selecting appropriate control measures. Additionally, disease classification aids in tracking the progression of diseases over time, which allows early prediction of outbreaks. For example, monitoring the spread of late blight in potato fields can help farmers take timely preventive actions. Moreover, classification supports recommending suitable disease control strategies, such as choosing specific pesticides, adopting biological control, or adjusting cultural practices to reduce disease incidence. It also assists in estimating crop loss by assessing the severity and potential impact of the disease. For instance, identifying a viral disease transmitted by whiteflies in cotton fields helps anticipate significant yield losses if not managed promptly. Among all classification methods, classification based on causative agents is considered the most modern and effective, enabling faster identification and decision-making. The classification based on disease symptoms or signs is also a reliable approach, especially useful for on-field diagnosis and immediate observation.

Advances in disease diagnosis

Molecular tools for early diagnosis

Molecular diagnostic techniques have significantly improved the accuracy and speed of plant disease detection. Polymerase chain reaction (PCR), quantitative real-time PCR (qPCR) and loop-mediated isothermal amplification (LAMP) are widely used to detect pathogen DNA or RNA with high specificity and sensitivity (Mirmajlessi *et al.*, 2015; Le and Vu, 2017; Hariharan and Prasannath, 2021). These methods allow for early detection of infections, often before visual symptoms appear. Next-

generation sequencing (NGS) further enhances diagnostic capabilities by enabling the detection of multiple pathogens in a single sample. Portable sequencing devices, such as the Oxford Nanopore MinION, have facilitated field-based pathogen detection, offering real-time diagnostic solutions (Mushtaq *et al.*, 2021).

Smart monitoring using imaging and AI

The general procedure execution of AI- algorithms is plotted in Fig 3. Remote sensing is a promising approach to plant disease detection. Technologies such as hyperspectral, multispectral and thermal imaging detect subtle changes in plant health (Chauhan *et al.*, 2024; Terentev *et al.*, 2022). Changes in leaf color, temperature, or water content can signal infection long before visible symptoms appear. Drones and satellites equipped with these sensors help monitor large areas (Hafeez *et al.*, 2022; Wang *et al.*, 2024).

The data is analyzed using machine learning algorithms, which have become essential tools for disease diagnosis. Convolutional neural networks (CNNs) are widely used for identifying plant diseases from images (Aishwarya *et al.*, 2024). In addition, more advanced models, such as deep residual networks (ResNet) and EfficientNet, are being explored for their higher accuracy and faster inference times (Li *et al.*, 2021). Transformer-based models like Vision Transformers (ViT) have also shown promise in handling complex image classification tasks (Dosovitskiy *et al.*, 2020). The combination of remote sensing, deep learning and cloud-based decision platforms revolutionize crop health monitoring. Farmers could receive real-time alerts and treatment recommendations via mobile apps, making disease management more proactive. Reinforcement learning and explainable AI are emerging trends that may enhance model reliability and farmer trust (Quach *et al.*, 2024). However, challenges such as image variability, environmental noise and limited labeled datasets remain. Recent efforts in data augmentation and transfer learning

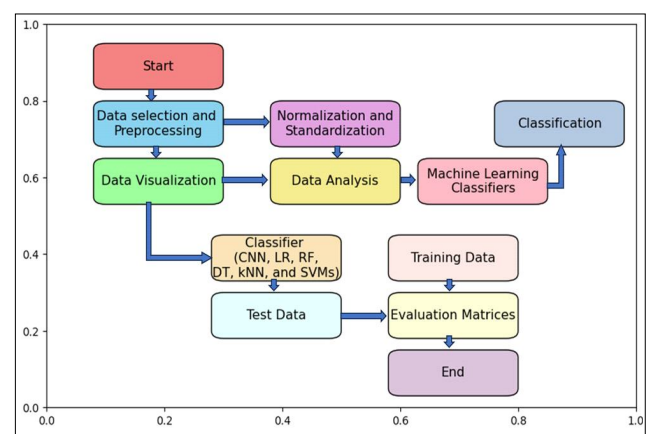


Fig 3: The general procedure followed for machine learning algorithms.

are helping address these issues (Khare *et al.*, 2024; Xu *et al.*, 2022).

Advances in disease management

Biological control agents

Biological control agents are a sustainable option for disease management. These include beneficial microorganisms like *Trichoderma* spp., *Bacillus* spp. and mycorrhizal fungi (Rahman *et al.*, 2017). They suppress pathogens, promote plant health and reduce the need for chemical pesticides. Research in microbial genomics has led to stronger and more effective biocontrol products. Multi-strain formulations help tackle a wider range of diseases. They also adapt better to different environmental conditions (Fira *et al.*, 2018).

Resistance breeding

Breeding disease-resistant crops is a key strategy in plant protection. Modern techniques speed up this process. Marker-assisted selection (MAS) and genomic selection (GS) help identify resistance genes (Varshney *et al.*, 2018). These genes are introduced into new crop varieties. Gene-editing technologies, such as CRISPR/Cas9, allow precise changes in plant genomes (Chen *et al.*, 2019). They enable the development of crops resistant to multiple pathogens. Stacking or pyramiding resistance genes improves long-term disease control. RNA interference (RNAi) is also used to silence harmful genes in pathogens.

CONCLUSION

The detection and management of plant diseases are vital for global food security and sustainable agriculture. Classifying plant diseases based on frequency, spread, host specificity and symptoms helps in understanding disease behavior and planning effective control measures. Advances in artificial intelligence and machine learning have improved disease detection through image analysis and data-driven models. These technologies allow for faster and more accurate diagnosis compared to traditional methods. Despite progress, there are limitations in current research. Many models use laboratory-based datasets that lack field variability. Changes in lighting, background conditions and symptom overlap affect accuracy. Most models are not validated across large scales or different crop types. Additionally, the lack of model interpretability reduces trust among farmers and agricultural professionals. Future research should focus on developing diverse, field-tested datasets that cover various disease stages and environmental conditions. Combining multiple data sources, including hyperspectral imagery, soil health and climate data, could enhance model performance. Efforts must also be made to design explainable AI systems with simple, user-friendly interfaces. Collaboration between plant scientists, data analysts and engineers will be crucial. Such partnerships can turn research advances into practical solutions that promote sustainable crop production and strengthen food security.

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Authors' contributions

All authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all the aspects of this work.

Data availability

The data analysed/generated in the present study will be made available from corresponding authors upon reasonable request.

Availability of data and materials

Not applicable.

Use of artificial intelligence

Not applicable.

Declarations

Authors declare that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

The authors declare that they have no conflict of interest.

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