

## Review

# A Review on Artificial Intelligence Methods for Plant Disease and Pest Detection

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## Abstract

Artificial intelligence (AI) has emerged as a transformative tool for plant health monitoring, offering new opportunities for scalable, timely, and data-driven pest and disease management in agriculture. This review provides a comprehensive synthesis of AI-based methods for pest and plant disease detection, systematically organizing existing literature across sensing modalities, learning paradigms, and deployment scales. We distinguish between population-level pest monitoring, plant-centric visual inspection, and field-scale surveillance, as well as between post-symptomatic disease recognition and pre-symptomatic detection enabled by spectral imaging technologies. Beyond summarizing recent advances, this work places strong emphasis on critical analysis, discussing fundamental limitations related to data scarcity, domain shift, generalization under field conditions, and the challenge of disentangling biotic from abiotic stress factors. The review further examines the distinction between correlation-driven AI predictions and causal disease understanding, positioning AI as a complementary decision-support tool alongside established diagnostic methods. Building on these insights, we outline key future research directions, including multimodal sensor fusion, explainable and trustworthy AI, edge-based deployment for real-time monitoring, and the development of foundation models for unified agricultural intelligence. This review aims to serve as both an accessible entry point and a critical reference for advancing AI-driven plant health management.

**Keywords:** Artificial Intelligence; plant health; precision agriculture; pest and disease detection; computer vision



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## 1. Introduction

Over the past few decades, the global agricultural sector has been confronted with rising food demand while grappling with limited resources and environmental constraints [1]. With the world's population projected to reach approximately 9.8 billion by 2050 [2,3], an unprecedented pressure mounts on agricultural systems to increase productivity and ensure food security. In light of this, plant diseases and pests have emerged as formidable threats, causing up to 40% of global crop losses annually [4,5]. **Plant health** extends beyond the mere absence of disease, encompassing physiological well-being where crops achieve optimal functioning while remaining free from **biotic stressors** (including pests such as insects, mites, and nematodes that cause feeding damage and disease vectoring,

and pathogens like fungi, bacteria, and viruses that disrupt cellular processes) and **abiotic stressors** such as drought, salinity, and nutrient deficiencies [6,7]. **Pests** cause direct physical damage through feeding, reduce photosynthetic capacity, create entry points for secondary infections, and serve as vectors for viral and bacterial pathogens [8], while **plant diseases** disrupt normal physiological processes by interfering with nutrient uptake, blocking vascular systems, and altering metabolic pathways, ultimately leading to yield losses and plant death [9]. Plant health management requires integrated approaches spanning disease detection [10], pest monitoring [11], nutrient optimization [12], and stress assessment [13]. However, timely discovery through conventional **phytosanitary measures** (regulatory procedures for preventing pest and disease spread through inspection, quarantine, and control [14]) presents significant challenges [15], as traditional methods often detect problems only after visible symptoms appear [16–20], when economic damage has occurred and intervention effectiveness is substantially reduced [21].

Plant health significance extends beyond agricultural productivity, encompassing global sustainability and human welfare. **Food security**, defined as ensuring adequate food availability, accessibility, utilization, and stability for all populations [22], becomes increasingly challenging as crops must meet rising global food demand without expanding agricultural land use [1,23]. **Food safety** focuses on preventing contamination, as diseased plants accumulate mycotoxins (toxic fungal metabolites posing health risks [24]), pathogens, and harmful compounds creating consumption risks [25]. **Human health** links to plant health management, where late disease detection triggers excessive pesticide applications, resulting in chemical residue accumulation and environmental contamination [26,27]. **Climate change** intensifies challenges by increasing disease pressure, accelerating pathogen evolution, and shifting pest geographical ranges, disrupting established protocols [28]. The economic losses are staggering: plant diseases and pests cause approximately \$220 billion in annual global crop losses [4,29], with fungal diseases accounting for \$60 billion [30], insect pests \$70 billion [31], and viral diseases \$30 billion [32]. These converging pressures create urgent need for innovative, technology-driven solutions transforming plant health monitoring.

Current plant health management relies on conventional approaches that present fundamental limitations hindering effective crop protection [33]. Traditional methods encompass visual inspection by agronomists [34], laboratory diagnostics including Polymerase Chain Reaction (PCR) for pathogen DNA detection [35] and Enzyme-linked immunosorbent assays (ELISA) for pathogen-specific protein identification [36], and field scouting within Integrated Pest Management (IPM) frameworks that combine biological, cultural, physical, and chemical control strategies [37]. While molecular diagnostics such as PCR are capable of detecting infections at pre-symptomatic stages, their effectiveness in real-world agricultural settings is constrained by sampling frequency, laboratory processing time, cost, and infrastructure requirements, limiting their scalability for continuous, field-wide monitoring [35]. More details in Section 3.1. Consequently, disease detection in practice often remains reactive rather than preventive, with interventions frequently initiated only after visible symptoms appear [16,18,34]. Manual visual inspection suffers from subjectivity, requires specialized expertise, and becomes labor-intensive across large cultivation areas [38]. Laboratory diagnostics further introduce delays and costs: PCR typically requires 24–72 h and specialized equipment costing \$15,000–\$150,000 [35], while culture-based methods are slow (5–14 days) and limited to culturable pathogens [39]. Field scouting within IPM frameworks remains largely symptom-driven, often missing early or spatially sparse infestations [37]. These practical constraints create a pre-symptomatic detection gap at scale, leading to delayed interventions, accelerated pathogen spread, substantial yield losses, and compensatory overuse of pesticides [21].

**Artificial Intelligence (AI)** represents a paradigm shift in plant health management, offering unprecedented capabilities to overcome the fundamental constraints of conventional diagnostic approaches [38,40,41]. At its core, Machine Learning (ML) enables computational systems to identify complex patterns within agricultural data without explicit programming by learning from training datasets to make predictions on new, unseen data [40], while Deep Learning (DL) leverages multi-layered artificial neural networks with multiple hidden layers to automatically extract hierarchical features from high-dimensional datasets that surpass human perceptual capabilities [40]. These technologies directly address critical agricultural challenges by automating complex analytical tasks, from processing multispectral imaging (capturing 3–12 spectral bands including visible and near-infrared light) [16,42,43] and hyperspectral imaging (recording hundreds of narrow spectral bands from 400–2500 nm to detect subtle biochemical changes invisible to conventional sensors) [42,43] to analyzing thermal signatures that reveal plant stress through leaf temperature variations [44] and integrating diverse sensor modalities including RGB cameras [20,45,46], LIDAR [47], and environmental sensors [48], pathogen lifecycle data [49], and plant physiological responses [41]. AI fundamentally overcomes traditional limitations through continuous monitoring capabilities using autonomous sensing platforms [50], elimination of subjective bias inherent in human visual assessment [16], and capacity for real-time analysis of sensor data at unprecedented scales covering large areas simultaneously [16]. The transformative benefits include early detection during the critical pre-symptomatic intervention window with 40–60% reduction in pesticide use through precision application [51], scalability through autonomous drone and robot platforms reducing monitoring costs significantly [50], and precision that enables targeted interventions [52], collectively positioning AI as the enabling technology for sustainable, data-driven crop protection strategies.

AI integration in agriculture represents **Agriculture 4.0** (the fourth agricultural revolution combining digital technologies, automation, and IoT connectivity for intelligent farming systems [53]) with disease and pest detection as the critical application for food security [54]. Precision agriculture leverages AI for site-specific monitoring through variable-rate systems [16,55], enabling targeted interventions based on real-time detection across heterogeneous conditions [4]. Smart farming integrates IoT sensors (networks of soil, weather, and camera devices collecting environmental data) with AI platforms, creating autonomous monitoring networks triggering precise interventions [56]. These technologies democratize access through smartphone applications and cloud platforms providing expert-level recognition regardless of location [48]. Laboratory research contributes to disease characterization, supporting European Green Deal (<https://cordis.europa.eu/project/id/101070496>, accessed on 2 July 2025) objectives by reducing pesticide use and improving ecosystem monitoring [57]. However, current applications focus on reactive detection after symptoms, representing gaps in proactive strategies requiring advanced methodologies for pre-symptomatic detection.

Recent reviews have examined various aspects of AI applications in plant health management. Jafar et al. [34] provides a broad overview of AI methods for plant disease detection, examining applications and limitations while highlighting AI's revolutionary potential. Attri et al. [58] offers an extensive survey of DL techniques in agriculture, covering AI applications from crop monitoring to yield prediction. Wang et al. [59] focuses on DL advances for plant disease and pest detection using remote sensing technologies, emphasizing satellite and aerial imagery integration with AI algorithms. Shoaib et al. [60] presents a coverage of DL approaches for plant disease and pest detection, providing detailed analysis of current methodologies. Aziz et al. [61] examines the revolutionary impact of remote sensing and AI in pest management. Dolatabadian et al. [62] provides focused coverage of image-based crop disease detection using ML, analyzing computer

vision approaches and their agricultural effectiveness. Minhans et al. [63] explores AI for plant disease management, examining technology integration with traditional practices. Khan et al. [64] offers detailed review of automated plant disease detection, examining motivations, limitations, and recent advancements. Mahlein et al. [65] presents comprehensive perspective on optical sensors, robots, and AI in modern plant disease management, bridging detection technologies with protection strategies. Liu and Wang [17] provides foundational coverage of plant diseases and pests detection based on DL, establishing early frameworks for understanding AI applications in agricultural diagnostics.

In contrast to these broader surveys, this review adopts a uniquely focused, prevention oriented perspective emphasizing AI's transformative potential for early detection in plant health management, moving beyond conventional reactive approaches. While previous reviews [34,58–60] predominantly examine AI applications across diverse agricultural domains or provide general overviews of post-symptomatic detection, this work specifically addresses the critical gap in early warning systems for plant health threats. Unlike reviews focusing on remote sensing applications [59,61] or general ML approaches [17,62], this review provides comprehensive coverage of current AI methodologies while uniquely emphasizing pre-symptomatic detection capabilities enabling intervention before visible symptom manifestation. This paradigm shift from reactive to proactive plant health management represents crucial advancement for addressing contemporary agricultural challenges, including emerging invasive species, climate induced pathogen evolution, and sustainable crop protection strategies minimizing chemical inputs while maximizing yield protection. By systematically examining AI's potential to achieve “seeing the unseen” through detecting plant health threats before economic damage occurs, this review establishes comprehensive foundation for understanding AI's role in preventing problems before they occur rather than detecting them after economic damage has begun.

The principal **contributions** of this review paper are summarized as follows:

- This review provides a structured and critical synthesis of AI-based approaches for pest and plant disease detection, organizing existing work across sensing modalities, learning paradigms, and deployment scenarios.
- The paper establishes a strong conceptual foundation by systematically introducing key terminology, sensing technologies, and ML principles relevant to agricultural AI, supported by a comprehensive background and introductory framework that enables clear interpretation of both classical and state-of-the-art methods.
- Unlike existing reviews that primarily examine post-symptomatic detection, this paper also systematically explores pre-symptomatic identification using advanced hyperspectral imaging, positioning AI as a technology capable of “seeing the unseen” before economic damage occurs and enabling proactive responses to emerging threats including invasive species and climate-induced pathogen shifts.
- A dedicated discussion is provided on the fundamental limitations of correlation-driven AI models in plant health applications, explicitly distinguishing predictive accuracy from causal understanding, and clarifying the role of AI as a decision-support tool that must be integrated with established diagnostic techniques such as PCR and ELISA for reliable disease confirmation.
- The review offers an in-depth analysis of key challenges hindering real-world adoption, including data scarcity, domain shift across crops and environments, limited model generalization under field conditions, and the difficulty of disentangling biotic from abiotic stress factors, positioning these limitations as central research problems rather than secondary implementation details.
- Building on this critical analysis, the paper articulates a forward-looking research agenda for agricultural AI, identifying open directions such as multimodal sensor

fusion, explainable and trustworthy AI for farmer and stakeholder adoption, edge computing for real-time in-field deployment, and the development of foundation models capable of generalizing across crops, tasks, and agro-ecological regions.

This review focuses on AI-based detection of pests and diseases in the crops most commonly studied in recent literature, notably tomato, cucumber, grape, potato, and pepper. AI-based monitoring has also been applied to cotton, rice, wheat, maize, and various fruit trees, as well as to less-studied pest categories such as whiteflies, mealybugs, and root-knot nematodes, but covering all crop-pest combinations is beyond the scope of this work. Representative studies are used to illustrate broader methodological trends, capabilities, and limitations. Readers interested in crop-specific surveys are directed to complementary reviews for remote-sensing-based applications [59], image-based disease detection [62], and general DL in agriculture [58].

The rest of this paper is organized as follows. Section 2 provides necessary background including plant health overview and AI fundamentals. Section 3 explores AI applications in plant health. Section 4 examines key challenges, limitations, and critical discussion. Section 5 suggests future research directions. Finally, Section 6 concludes the paper.

## 2. Background

### 2.1. Plant Health Fundamentals

Plant health assessment represents a critical challenge in modern agriculture, where accurate identification of stress factors determines the success of intervention strategies and ultimately crop productivity. Understanding the complex interplay of biotic and abiotic stresses, their symptom manifestation patterns, and environmental influences provides the foundation for developing effective AI-based detection systems.

Biotic stresses in plants arise from living organisms and can be systematically categorized by pathogen type, each presenting distinct symptoms and diagnostic challenges. **Fungal pathogens** represent the most widespread category, responsible for approximately 70–80% of all plant diseases globally [66], with over 8000 species causing devastating agricultural losses [67]. Common fungal diseases include powdery mildew characterized by white, powdery growths on leaf surfaces, rust diseases presenting as orange to brown pustules, and various blight conditions causing rapid browning and tissue death. **Bacterial pathogens** such as *Pseudomonas* and *Xanthomonas* species create water-soaked lesions, angular leaf spots confined by leaf veins, and systemic wilting through vascular colonization [68]. Fire blight exemplifies bacterial disease severity, causing rapid shoot blackening that resembles fire damage [69]. **Viral pathogens** manifest through distinctive symptoms including mosaic patterns, yellowing, chlorosis, stunting, and necrosis [70]. **Insect pests** cause damage through direct feeding, creating shot holes, defoliation, and stippling damage from sucking insects like aphids and thrips, while also serving as vectors for pathogen transmission. **Nematodes** present unique challenges as microscopic roundworms causing root galling, lesions, and systemic plant stunting. Examples of such pathogens include root-knot nematodes, which create characteristic root galling [71].

Abiotic stresses encompass non-living environmental factors that limit plant growth and development, often creating symptoms that overlap significantly with biotic stress manifestations. **Drought stress** occurs when water scarcity limits cellular function, triggering ABA-mediated stomatal closure, osmotic adjustment through proline and glycine betaine accumulation, and activation of dehydration-responsive genes [72]. Visual markers include leaf rolling, wilting, and early senescence, accompanied by reduced chlorophyll content [73]. **Temperature extremes** manifest differently depending on severity and duration, with heat stress causing leaf curling, blossom drop, and sunscald on fruit surfaces, while activating heat shock proteins for cellular protection. Cold stress induces chilling

injury below 12–15 °C and freezing damage at sub-zero temperatures, creating necrotic lesions and membrane disruption [74]. **Salinity stress** results from excessive Na<sup>+</sup> and Cl<sup>−</sup> accumulation, creating both osmotic stress and ion toxicity, with plants exhibiting chlorosis and growth reduction [75,76]. **Nutrient deficiency and toxicity** present complex symptom patterns in plants, with nitrogen deficiency causing chlorosis and yellowing in older leaves, phosphorus deficiency creating purplish-red discoloration due to anthocyanin accumulation, iron deficiency manifesting as interveinal chlorosis in young leaves, and boron toxicity resulting in leaf necrosis beginning at tips and margins [77]. **Pollution stress** from heavy metals induce chlorosis and root damage through oxidative stress mechanisms [78].

Furthermore, there are complex interactions between biotic and abiotic stresses. Climate change significantly amplifies stress interactions, creating synergistic effects that exceed predictions from individual stress studies. Research demonstrates that combined drought and pathogen infection produces enhanced disease severity through multiple mechanisms, with drought acting as a predisposing factor that compromises plant immunity while creating favourable conditions for pathogen development [72]. Temperature increases of 2.4–4 °C predicted by 2100 will affect 76% of global land area, intensifying “hotter droughts” that combine water limitation with thermal stress [79]. **Visual distinction between biotic and abiotic stresses** presents significant challenges, as both can cause wilting, yellowing, necrosis, and growth reduction [80]. However, diagnostic patterns emerge: abiotic stresses typically generate even symptom gradients that correlate with environmental factors, while biotic stresses often present scattered or rough gradient patterns with pathogen-specific features such as fungal fruit bodies or insect damage [80].

Table 1 lists visual symptoms shared between biotic and abiotic stress factors and the discriminating features AI-based systems can exploit.

**Table 1.** Visual symptoms shared between selected biotic and abiotic stress factors, and features used by AI systems to differentiate them.

| Symptom        | Biotic Causes             | Abiotic Causes              | Discriminating Features for AI                                                                |
|----------------|---------------------------|-----------------------------|-----------------------------------------------------------------------------------------------|
| Leaf yellowing | Viral infection, root rot | N deficiency, waterlogging  | Spatial distribution (patchy vs. uniform gradient); lesion boundary sharpness                 |
| Leaf necrosis  | Fungal blight, bacteria   | Salt toxicity, frost damage | Lesion shape regularity; presence of fungal sporulation at lesion border                      |
| Wilting        | Vascular wilt pathogens   | Drought, heat stress        | Symptom pattern (one-sided vs. whole-plant); spatial correlation with soil moisture gradients |
| Chlorosis      | Virus, Phytoplasma        | Fe/Mn deficiency            | Interveinal vs. diffuse distribution; spectral response at 550–670 nm                         |
| Stunting       | Nematodes, viruses        | Salinity, compaction        | Root galling (if visible); spatial correlation with soil EC patterns                          |

Plant stress responses follow a predictable temporal progression from invisible molecular changes to visible tissue damage, creating critical intervention windows for effective management [16]. Molecular and cellular changes occur within minutes to hours of stress onset, including transcription factor activation (NAC, WRKY, MYB families), shifts in hormone levels (e.g., ABA, jasmonic acid, and salicylic acid), changes in protein synthesis, and ROS accumulation. These invisible changes represent the earliest stress indicators

but require sophisticated detection methods. Physiological changes become detectable by sensors within 30 min to 24 h, with chlorophyll fluorescence parameters like Fv/Fm (maximum quantum efficiency of PSII) showing stress detection capability within 15–30 min of pathogen infection by *Botrytis cinerea* or *Spodoptera exigua* feeding damage [81]. Spectral reflectance alterations in near-infrared and visible wavelengths, thermal signatures from altered transpiration, and water status indicators provide sensor-detectable markers before visual symptoms appear. Visual symptoms manifest 3–21 days after stress onset, progressing from subtle color changes through morphological alterations to tissue damage and structural failure [82].

Early detection of plant stresses provides substantial economic benefits through yield loss prevention and reduced management costs [83]. Global statistics reveal that plant diseases cause annual worldwide losses of up to 40% for maize, potato, rice, soybean, and wheat crops [84]. Direct economic impacts include \$220 billion annually from plant diseases globally, with virus damage alone exceeding \$30 billion worldwide [84].

Early detection systems provide documented cost savings of \$2400 per hectare annually for esca and leaf-roll diseases in vineyards, while production costs increase up to 60% per infected hectare when detection occurs after symptom development. Technology requirements for pre-symptomatic detection include chlorophyll fluorescence systems focusing on qp (fraction of open PSII reaction centers) as the most sensitive early indicator [81], multispectral imaging across VIS-NIR-SWIR domains (400–2500 nm), and integrated multi-sensor platforms combining thermal, fluorescence, and spectral data.

Different growing environments present unique challenges for plant health assessment and technology deployment, requiring specialized approaches for effective monitoring. Laboratory conditions provide controlled environments ideal for establishing baseline stress responses and validating detection methods, but lack representativeness of real-world agricultural conditions, limiting direct applicability to field scenarios. Greenhouse environments offer semi-controlled validation with manageable environmental variables while introducing microclimatic heterogeneity, serving as important intermediate steps for technology development. Open field conditions present real-world complexity with multiple interacting weather variables, soil heterogeneity, and natural pest/pathogen pressure, requiring robust calibration protocols and environmental compensation algorithms. Pot and parcel experimental systems provide intermediate scaling opportunities but face limitations in representing field-scale pathogen pressure and environmental gradients. Indoor versus outdoor considerations affect pathogen development patterns, with indoor systems showing more predictable disease progression but potentially missing important environmental triggers, while outdoor systems require accounting for weather-dependent pathogen lifecycle timing and vector activity patterns [85].

Environmental conditions significantly influence both disease development patterns and sensor performance, creating complex interactions that must be addressed for successful technology deployment [16]. **Disease development and pathogen spread** vary dramatically with environmental conditions, as demonstrated by temperature-dependent pathogen virulence where many pathogens cannot cause infections above specific thresholds, while humidity levels affect spore germination and dispersal patterns. Wind patterns influence spore dispersal modeling and require consideration in predictive algorithms, while soil conditions affect root health assessment capabilities and sensor placement strategies. **Sensor performance and calibration** face environment-specific challenges, with light conditions significantly affecting imaging and spectral analysis accuracy, requiring adaptive algorithms for varying illumination. Temperature and humidity fluctuations cause sensor drift, necessitating frequent calibration protocols and environmental compensation methods, while weather events like rain and dust affect sensor window cleanliness and data

quality [86]. **AI model accuracy and generalization** show significant degradation when deployed across different environmental conditions, with models trained in controlled environments often requiring retraining or domain adaptation for field deployment. Research demonstrates that environmental variability affects spectral signatures and thermal patterns used for disease detection, requiring robust data fusion approaches that integrate multiple sensor modalities [38]. **Practical deployment strategies** must account for these environmental challenges through adaptive algorithms that compensate for environmental variability, regular calibration schedules appropriate for local conditions, and model architectures designed for environmental robustness. Successful systems employ hierarchical approaches that combine multiple sensor types, implement environmental monitoring for context-aware analysis, and utilize local adaptation strategies to maintain accuracy across diverse growing conditions [87].

The integration of these fundamental plant health concepts provides the scientific foundation necessary for developing robust AI-based detection systems capable of early, accurate stress identification across diverse agricultural environments. Understanding the complex interplay of biotic and abiotic factors, their temporal development patterns, and environmental influences enables the design of more effective monitoring technologies that can substantially reduce global crop losses through timely intervention strategies.

One of the biggest challenges with current AI models is the fact that they have been trained on data sets that were collected at a single point of stress (i.e., single-stress) but that does not take into account the multiple points of stress that plants may be experiencing in a real-world environment. This makes multi-tasking learning methods using both the classification of stress types and the prediction of the level of stress useful to steer the model towards more relevant characteristics (i.e., what is important to know about a stressed plant), as opposed to just visual characteristics [80]. The use of physics-based networks that incorporate the biological properties of plants such as their expected spectral responses to biotic vs. water stress when calculating losses also offer a path forward for developing more understandable representations of plant health.

## 2.2. Artificial Intelligence Fundamentals

The term Artificial Intelligence (AI) encompasses the entire area of research into developing systems that are able to act intelligently. AI is an extremely broad field. Machine Learning (ML) is one subset of the area of research into AI where systems learn patterns from inputted data and do so in a way that does not need explicitly defined programming. There are many different types of ML techniques including Support Vector Machines (SVM), Decision Trees, Random Forests, Kernel-Based Classifiers etc. Deep Learning (DL) is a subset of ML where the method used to train the model utilizes multi layered Neural Networks to create hierarchical representations of the data it is being trained on. A major difference between traditional ML and DL is that when using DL, features are learned end-to-end by the model from raw input data whereas, when utilizing traditional ML approaches, feature extraction is often required prior to running the classification or regression algorithm. In addition, traditional ML algorithms are commonly utilized for agricultural applications where pre-extracted features such as Spectral Indices and Texture Descriptors have already been extracted from images taken with a multispectral camera or other type of camera. On the other hand, DL architectures such as CNN and Vision Transformer learn from raw pixel values, hyperspectral cubes, or time-series data from sensors [40].

Computer vision is a field that develops computational techniques to acquire and analyze visual information in images and videos with the aim of automating tasks ordinarily performed by human vision. In the modern DL era, computer vision leverages DL to

automatically learn features from image data, enabling tasks such as image classification, object detection, and region segmentation [88]. An image classifier assigns each image to one of two or more pre-specified classes, and system performance is evaluated using metrics such as accuracy, precision, recall, and F1 score [88]. In addition, detection and localization networks employ bounding boxes to detect and locate objects within images, with real-time processing capabilities considered essential for successful field deployment [88]. These detection systems are commonly evaluated using metrics such as mean Average Precision (mAP) and Intersection over Union (IoU) [88]. Image segmentation provides pixel-level disease mapping by classifying every pixel in the image and producing a detailed segmentation map, with segmentation accuracy typically evaluated using the IoU metric [88]. Instance segmentation extends semantic segmentation by distinguishing individual object instances within the same class, enabling precise delineation of multiple objects of identical categories, while panoptic segmentation unifies semantic and instance segmentation by assigning each pixel both a semantic class label and an instance identity, thereby providing holistic scene understanding of both foreground objects and background regions [88]. Lastly, regression models are used to quantify continuous outcomes such as yield loss estimates and disease spread modeling [88].

Neural network architecture design remains an evolving research area. Early advances in computer vision were driven by Convolutional Neural Networks (CNNs). CNNs employ convolutional filters to identify patterns in localized image regions [89]. Notable CNN architectures include AlexNet [90], VGGNet [91], and ResNet [92]. In contrast to CNNs, Vision Transformers (ViTs) [93] capture global context by treating images as sequences of patches and applying the self-attention mechanism, which allows each patch to attend to and weigh the importance of all other patches in the image [94].

As previously mentioned, object detection is a fundamental computer vision task in which a network is trained to identify multiple instances of objects within an image. Several architectures have been developed for this purpose, each with its own strengths and trade-offs. The three main families of object detection architectures are R-CNN [95], YOLO [96], and SSDs [97]. R-CNN applies a pre-trained CNN to candidate object regions for its final predictions [95]. The YOLO and SSD architectures prioritize real-time performance by processing the entire image at once [96,97].

In semantic segmentation, a semantic class label is predicted for each pixel in an image without distinguishing between individual object instances. Instance segmentation extends this formulation by assigning separate instance identities to objects of the same class, while panoptic segmentation unifies semantic and instance segmentation by jointly labeling every pixel with both a class and an instance identifier. A variety of DL architectures have been proposed to address these segmentation tasks. UNet is a convolutional neural network with a symmetric encoder–decoder architecture originally developed for biomedical semantic segmentation [98]. DeepLab is a family of convolutional architectures that leverage atrous (dilated) convolutions and multi-scale context aggregation to improve semantic segmentation performance [99]. Mask R-CNN extends region-based object detection frameworks by incorporating a parallel mask prediction branch, enabling high-quality instance segmentation [100]. More recently, unified architectures such as Mask2Former have demonstrated the ability to perform semantic, instance, and panoptic segmentation within a single framework [101]. In addition, modern detection-based models such as YOLO have been extended beyond object detection to support instance segmentation through mask prediction heads, enabling efficient real-time segmentation [102].

Various imaging modalities are used to capture different types of information from plant surfaces. The most common modality is RGB imaging, which captures visual information in the Red, Green, and Blue channels, closely resembling human vision [103]. RGB

imaging is intuitive, cost-effective, and widely accessible, making it suitable for integration into smartphones and other portable devices [103]. However, since it captures only the visible spectrum, RGB imaging is limited to detecting plant diseases and symptoms visually apparent to the human eye [103]. Beyond RGB, hyperspectral and multispectral imaging technologies capture visual information across multiple narrow spectral bands [103]. Hyperspectral imaging records dozens to hundreds of these bands, while multispectral imaging typically uses 3 to 13 selected bands, including RGB, red edge, and near-infrared [103]. In contrast to RGB imaging, hyperspectral and multispectral imaging can detect subtle physiological changes at earlier stages [103]. However, their higher cost and complexity hinders their widespread adoption in resource-constrained agricultural settings [103]. Other notable modalities include thermal and fluorescence imaging, which measure temperature anomalies on plant surfaces and disruptions in photosynthetic activity, respectively [103].

Robotics and Internet of Things (IoT) technologies are increasingly deployed for plant health monitoring [104]. Drones, which can be equipped with RGB, multispectral, or hyperspectral cameras, enable large-scale aerial imaging, facilitating fast crop health assessments over wide areas [104]. On the ground, proximal sensing platforms such as autonomous robots capture high-resolution images and sensor readings closer to the plant canopy, improving the detection of fine-scale symptoms [104]. Complementing these visual sensing systems, IoT networks deploy environmental sensors in the field to measure variables such as soil moisture, temperature, and humidity [104]. These measurements offer valuable context for plant health imaging data [104]. Together, these technologies support precision agriculture by enabling real-time monitoring and data-driven decision-making.

### 2.3. Validation and Performance

Adequate evaluation of plant-disease/pest detection models will require benchmarking within controlled environments, as well as against real-world applications. The first key component for model evaluation is establishing “ground truth.” With respect to detecting disease symptoms in images via bounding-boxes or pixel-level-masks, this is done by expert phytopathologist annotators. Annotator agreement can be quantitatively assessed using Cohen’s Kappa statistic or Fleiss’ Kappa statistic. Ground-truthing is much more difficult when utilizing spectral imaging to detect disease before visual symptoms appear. Spectral signatures have been annotated as indicating disease presence (infection), however these signatures were obtained from an experimentally controlled environment where pathogens were introduced into plants and their presence confirmed through either Polymerase Chain Reaction (PCR) or Enzyme Linked Immunosorbent Assay (ELISA) at various times post-inoculation. This method ensures that any spectral signature annotated as infected corresponds to the presence of a pathogen and not some form of abiotic stress.

Laboratory-based testing provides a baseline for evaluating a model’s performance in a controlled environment. However, laboratory-based testing does not provide the level of variability in terms of image quality (background clutter), lighting (illumination variations), and symptoms observed in the field [105]. Therefore, it is essential to validate a model in the field prior to deployment. One additional way to evaluate a model’s performance is cross-domain validation. In this type of validation, a model is evaluated on a dataset from a domain other than that which it was originally developed to operate within (region, cultivar, etc.). Cross-domain validation provides the most challenging and realistic assessment of a model’s performance [106].

### 3. AI Applications in Plant Health

#### 3.1. Traditional Methods

Traditional plant disease detection and diagnosis in agricultural systems have historically relied on established methodologies refined over decades of agricultural practice [21]. Common methods include manual visual assessment, microscopic evaluation of morphology features to identify pathogens, as well as molecular and serological diagnostic techniques [10,107]. These techniques form the foundation of modern digital agriculture, but also highlight limitations in scalability.

Visual inspections through field scouting are the cornerstone of plant health monitoring, and involve trained personnel scouring through the field, observing individual parts of plants for symptoms of disease, pest infestation and nutrient deficiencies. This hands-on approach does not usually involve specialized technology, making it accessible to resource-limited farmers. That said, the reliability of this technique is solely based on the observer's expertise, and thus potentially leading to misclassifications of early or subtle symptoms [107].

Serological and molecular diagnostic methods have emerged as more sophisticated traditional approaches for pathogen identification [45,108]. ELISA and other immunological techniques have been widely adopted for detecting specific plant viruses and bacteria by targeting pathogen-specific proteins or antigens. These methods have proven particularly valuable for detecting systemic infections that may not yet show visible symptoms. PCR techniques and DNA-based identification methods have become increasingly important for accurate pathogen identification, particularly for distinguishing between closely related species or strains. More recently, isothermal amplification methods such as Loop-Mediated Isothermal Amplification (LAMP) have emerged as lower-cost, portable alternatives compatible with field deployment, reducing costs to the \$500–\$5000 and enabling pathogen detection without specialized laboratory equipment [109].

Despite their historical importance and continued relevance, traditional plant disease detection methods face significant limitations that have become increasingly apparent as agricultural systems demand faster, more accurate, and scalable diagnostic solutions. Visual inspection is prone to error due to symptom variability, limited evaluator expertise, and its time-intensive, poorly scalable nature. More advanced traditional approaches depend on costly equipment, specialized knowledge, and lengthy processing pipelines, which hinder their practical deployment at scale.

These limitations in conjunction with the evolution of AI-driven technologies have spurred the adoption of new innovative solutions for rapid, accurate, and scalable plant health monitoring.

#### 3.2. Pest Detection Methods

Pests are responsible for an estimated 20–40% of global crop yield losses annually, with insects (e.g., aphids, whiteflies, leafhoppers, planthoppers), mites, and nematodes acting not only as direct consumers but also as vectors for plant pathogens [110]. The threat posed by these organisms is exacerbated by rapid population growth, as in the case of aphids with multiple generations per year [110], their small physical size [111], high intra-species visual variability, and camouflage strategies that challenge human and machine perception alike [112].

Within this context, AI-based pest detection aims to enable timely and scalable surveillance, supporting early intervention and reducing reliance on blanket or pre-emptive pesticide application [111]. To this end, a diverse range of AI-driven solutions has emerged, leveraging computer vision, IoT-enabled sensing, robotic platforms, unmanned aerial vehi-

cles, and environmental data analysis. A structured overview of representative approaches is provided in Table 2.

**Table 2.** Summary of AI-based pest studies in crops. **Abbreviation legend:** *Environment*: G = Greenhouse, OF = Open Field. *Data*: RGB = Red-Green-Blue imaging, Sensor = Environmental sensors. *Task*: Det = Detection, Seg = Segmentation, Cls = Classification, For = Forecasting. Pest species are listed by their scientific (Latin) name; where the original study identified organisms at genus or family level, the highest available taxonomic resolution is retained.

| Ref   | Crop                                          | Pest                                                                                                                                                | Env. | Data          | Task       | Method                                | Outcome                  |
|-------|-----------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------|------|---------------|------------|---------------------------------------|--------------------------|
| [111] | Tomato                                        | <i>Tuta absoluta</i>                                                                                                                                | G    | RGB<br>Sensor | Det<br>For | YOLOv10<br>ARIMAX                     | 89.1% mAP50<br>75.61 MSE |
| [113] | Tomato                                        | <i>Tuta absoluta</i>                                                                                                                                | G+OF | RGB<br>Sensor | Det<br>For | YOLOv8<br>ARIMAX                      | 97.6% mAP50<br>36.69 MSE |
| [114] | Tomato                                        | <i>Tuta absoluta</i>                                                                                                                                | G+OF | RGB           | Det        | Faster R-CNN<br>RetinaNet<br>Ensemble | 70% mAP                  |
| [115] | Cherry Tom.<br>Strawberry<br>Tomato<br>Cherry | <i>Bemisia</i> / <i>Trialeurodes</i> spp.<br>Agromyzidae spp.<br>Aphididae spp.<br>Tephritidae spp.<br><i>Thrips</i> spp.<br><i>Musca domestica</i> | G    | RGB           | Det        | YOLOv5                                | 96% Precision            |
| [116] | Soybean                                       | <i>Aloa lectinea</i><br><i>Eocathecona furcellata</i><br><i>Maruca vitrata</i><br><i>Spodoptera</i> spp. larvae<br><i>Leptocorisa oratorius</i>     | OF   | RGB           | Det        | YOLOv5                                | 99.5% mAP                |
| [117] | Grape                                         | Aphididae spp.<br>Lepidoptera larvae<br>Pseudococcidae spp.<br>Acari spp.<br>Stem borers<br><i>Thrips</i> spp.                                      | OF   | RGB           | Det        | YOLOv4                                | 84.41% mAP               |
| [118] | Potato                                        | <i>Leptinotarsa decemlineata</i>                                                                                                                    | OF   | RGB           | Cls        | DenseNet121                           | 96.30% accuracy          |
| [119] | Tomato                                        | <i>Dolycoris baccarum</i>                                                                                                                           | OF   | RGB           | Det        | YOLOv8                                | 98.75% mAP50             |
|       |                                               | <i>Phyllotreta</i> spp.                                                                                                                             |      |               | Seg        |                                       | 99.38% mAP50             |
|       |                                               | <i>Nezara viridula</i>                                                                                                                              |      |               |            |                                       |                          |
|       |                                               | <i>Myzus persicae</i>                                                                                                                               |      |               |            |                                       |                          |
|       |                                               | <i>Bemisia tabaci</i>                                                                                                                               |      |               |            |                                       |                          |
|       |                                               | <i>Leptinotarsa decemlineata</i>                                                                                                                    |      |               |            |                                       |                          |
| [119] | Tomato                                        | <i>Tuta absoluta</i>                                                                                                                                | OF   | RGB           | Det        | YOLOv8                                | 70.2% mAP50              |
|       |                                               | <i>Helicoverpa armigera</i>                                                                                                                         |      |               |            |                                       |                          |
|       |                                               | <i>Liriomyza bryoniae</i> (dmg.)                                                                                                                    |      |               |            |                                       |                          |
|       |                                               | <i>Frankliniella occidentalis</i> (dmg.)                                                                                                            |      |               |            |                                       |                          |
| [120] | Tomato                                        | <i>Tuta absoluta</i>                                                                                                                                | G    | RGB           | Det        | YOLOv8                                | 70.2% mAP50              |

From a methodological perspective, AI-based pest detection can be viewed as a progression across three increasingly complex levels of observation: (i) indirect, population-level monitoring through traps, (ii) direct, plant-centric detection of pests or infestation symptoms, and (iii) scalable field-level surveillance using aerial or wide-area sensing. Re-

cent work further explores hybrid frameworks that integrate multiple levels of observation to better support operational pest management.

### 3.2.1. Trap-Based Pest Monitoring and Forecasting

Trap-based monitoring represents one of the earliest and most widely adopted paradigms in AI-driven pest detection. In this setting, insects are detected indirectly using adhesive traps, allowing population dynamics to be estimated over time with minimal disturbance to crops. Kapetas et al. [111] introduced two AI-based systems for monitoring *Tuta absoluta* in tomato crops using glue-paper traps and YOLO-based object detection. Their initial study combined image-based pest counts with time-series analysis and environmental data, such as temperature and humidity, to forecast population trends over short temporal horizons. Building on this work, Kapetas et al. [113] developed an IoT-enabled trapping system capable of automated image acquisition and processing without human intervention, improving scalability and operational efficiency.

Moving beyond single-species monitoring, Zhang et al. [115] demonstrated multi-pest recognition by deploying yellow sticky traps equipped with automated imaging in greenhouse environments. Their approach illustrates how trap-based systems can be extended to more complex pest communities while retaining the advantages of controlled backgrounds and consistent viewpoints.

Overall, trap-based methods offer robustness and scalability for population monitoring and forecasting. However, their indirect nature limits spatial specificity and does not provide direct information about localized crop damage or infestation severity at the plant level.

### 3.2.2. Plant-Centric Detection of Pests and Infestation Symptoms

In contrast to trap-based monitoring, plant-centric approaches aim to detect pests or visible infestation symptoms directly on crops, enabling more localized and actionable decision-making. Mudegol et al. [117] investigated RGB-based pest detection on grape plants, constructing a dataset spanning multiple insect categories and demonstrating the feasibility of direct visual recognition under controlled conditions.

Rather than detecting insects themselves, Giakoumoglou et al. [114] focused on identifying infestation symptoms caused by *Tuta absoluta* on tomato plants, evaluating multiple object detection architectures to localize damaged regions. Similarly, Christakakis et al. [120] introduced a smartphone-based citizen science application in which user-captured images are analyzed using a YOLO-based model for automated pest and disease identification, highlighting the potential of participatory data collection.

More recent work has moved toward unified plant-centric frameworks capable of addressing multiple pest species and damage types within a single pipeline. Liu and Wang [121] used a shared YOLO-based architecture to detect both diseases and pests in greenhouse tomatoes; since most target classes are diseases, this study is listed in Table 3. Şahin et al. [119] proposed a two-stage system combining insect detection with leaf-damage segmentation across multiple pest and damage classes. Notably, their framework also incorporated a large language model to generate concise, human-readable explanations and management recommendations.

Despite their potential for precise intervention, plant-centric approaches remain challenging due to occlusion, background clutter, varying illumination, and the visual similarity between pests and plant structures. These factors contribute to reduced robustness when models are deployed under diverse field conditions.

**Table 3.** Summary of AI-based disease studies in crops. **Abbreviation legend:** *Environment:* G = Greenhouse, OF = Open Field, Lab = Laboratory. *Data:* RGB = Red-Green-Blue imaging, HS = Hyperspectral, MS = Multispectral. *Task:* Det = Detection, Seg = Segmentation, Cls = Classification. Disease entries use disease name as the primary identifier; where the causative pathogen is the standard reference in the literature (e.g., *Botrytis cinerea*), the pathogen name is retained. <sup>†</sup> [121] also detects *Agromyzidae* spp. (leaf miners) and *Trialeurodes vaporariorum* (greenhouse whitefly) within the same unified model.

| Ref   | Crop     | Disease                                                                                                                                                                   | Env. | Data   | Task                         | Method                        | Outcome                        |
|-------|----------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------|--------|------------------------------|-------------------------------|--------------------------------|
| [122] | Cucumber | Downy mildew<br>Powdery mildew (leaf)<br>Powdery mildew                                                                                                                   | G+OF | RGB    | Det                          | YOLOv8                        | 86.1% mAP50                    |
| [123] | Grape    | Anthraxnose<br>White rot<br>Gray mold<br>Powdery mildew                                                                                                                   | OF   | RGB    | Det                          | YOLO                          | 90.67% mAP50                   |
| [124] | Potato   | Anthraxnose<br>Early blight<br>Late blight                                                                                                                                | Lab  | HS     | Seg                          | Atrous-CNN                    | 99.88% precision               |
| [125] | Cucumber | Target spot<br>Leaf miner damage                                                                                                                                          | G    | RGB    | Seg                          | YOLOv8                        | 75.2% mAP50                    |
| [126] | Tomato   | Late blight<br>Gray leaf spot<br>Brown rot<br>Leaf mold                                                                                                                   | G    | RGB    | Det                          | Swin-DETR                     | 92.3% mAP                      |
| [121] | Tomato   | Early blight<br>Late blight<br>Yellow leaf curl virus<br>Brown spot<br>Gray mold<br>Leaf mold<br>Navel rot<br>Leaf curl disease<br>Mosaic<br>+2 pest classes <sup>†</sup> | G    | RGB    | Det                          | YOLOv3                        | 92.39% mAP                     |
| [19]  | Cucumber | <i>Botrytis cinerea</i>                                                                                                                                                   | Lab  | RGB+MS | Det                          | YOLOv7                        | 88.2% mAP50                    |
| [20]  | Cucumber | <i>B. cinerea</i> (early stage)<br><i>B. cinerea</i> (late stage)                                                                                                         | Lab  | RGB+MS | Seg                          | U-Net++                       | 87.7% Dice coeff.              |
| [45]  | Tomato   | Gray mold (early stage)<br>Gray mold (late stage)                                                                                                                         | Lab  | RGB+MS | Cls<br>Seg<br>Descriptor Cls | YOLOv8<br>Transformer<br>LSTM | 81.7% mAP50<br>79.41% accuracy |
| [46]  | Pepper   | <i>B. cinerea</i> (early stage)<br><i>B. cinerea</i> (late stage)                                                                                                         | Lab  | RGB+MS | Cls<br>Seg<br>Descriptor Cls | YOLOv8<br>Transformer<br>LSTM | 86.4% mAP50<br>87.2% accuracy  |

### 3.2.3. Field-Scale and Aerial Pest Detection

To address scalability in large and heterogeneous agricultural landscapes, several studies have explored field-scale and aerial pest detection using wide-area imaging. Verma et al. [116] collected RGB imagery across open-field soybean farms to detect multiple insect species under diverse environmental conditions, demonstrating the feasibility of large-scale visual monitoring. Similarly, Karakan [118] employed drone-based imaging to identify potato beetle infestations in open fields, leveraging high-resolution aerial imagery analyzed with DL models.

These approaches highlight the potential of UAV-based systems for rapid and wide-area pest surveillance. However, the elevated viewpoint and region-level analysis inherently limit fine-grained localization and symptom characterization, positioning aerial methods primarily as complementary tools for large-scale monitoring rather than substitutes for plant-level diagnosis.

#### 3.2.4. Spatial Scale Considerations in Pest and Disease Detection

Spatial scale of AI-based plant health monitoring affects sensor choice, model design, and kind of information that can be used to develop action plans.

Monitoring at the leaf-level offers the best resolution with respect to spatial detail for plant disease detection, involves close-ranged cameras using RGB or spectral data on robotic platforms or imaging stations. This level of analysis allows models to identify individual lesions, determine their area, and differentiate between types of diseases based upon texture and color. Hyperspectral imagery is being used for early-detection of symptoms prior to visible lesion formation by capturing physiological changes at a centimeter-scale resolution [19,20].

Monitoring at the plant-level covers individual crop plants; greenhouse robotic systems and drone imagery are common applications for defoliation assessment, wilting scoring, and multi-lesion severity mapping. At this level, models can use canopy context such as whether symptoms are limited to the lower canopy, which may indicate soil-borne pathogens, or spread throughout the entire canopy, which indicates airborne pathogens.

Monitoring at the canopy-level consists of multiple plants within one row or growing unit, typically used for trap-based population monitoring (Section 3.2), and drone-based field surveys support development of spatial maps reflecting infection pressure to guide targeted application. Regional-scale monitoring utilizes satellite and high-altitude aerial imagery, better suited for providing early warning of disease fronts and invasive species spreading than for managing crops at the individual level.

Transitioning from one spatial scale to another involves more than just image resolution; differences between sensing platforms, model architectures, annotation strategies, and ground truth methods have been identified. While most reviewed studies were conducted at either leaf or plant levels, fewer studies investigated the challenges associated with scaling up to regional deployment. Therefore, it is encouraged that all future benchmarks report the spatial scale of evaluation as standard metadata.

#### 3.3. Disease Detection Methods

Plant diseases constitute a major threat to global food security, with annual crop yield losses estimated to reach up to 40% worldwide, corresponding to hundreds of billions of dollars in economic impact [5]. Severe diseases such as citrus greening (HLB), potato late blight, and viral mosaic infections can cause substantial yield reductions and, in extreme cases, complete crop failure [110]. A defining challenge in disease management is the temporal progression of infection: many pathogens remain latent during early growth stages [124], exhibit subtle or ambiguous early symptoms that are difficult to detect visually [62], and often present overlapping symptom patterns across different diseases, complicating accurate diagnosis [127].

These challenges are further intensified by climate change, which is expected to increase disease incidence, alter pathogen lifecycles, and facilitate the introduction of new pathogens into previously unaffected regions. In this context, AI-based disease detection offers the potential for timely, scalable, and cost-effective identification of plant diseases, complementing traditional inspection methods that are labor-intensive, subjective, and error-prone [34]. Importantly, AI systems enable a shift from reactive disease iden-

tification toward proactive monitoring, supporting precision agriculture through earlier intervention and improved disease management [38].

From a methodological perspective, AI-based disease detection approaches can be broadly categorized according to the stage of infection they target: (i) post-symptomatic detection using visible-spectrum imaging, and (ii) pre-symptomatic detection leveraging spectral imaging modalities capable of capturing latent physiological changes. An overview of representative methods is provided in Table 3.

### 3.3.1. Post-Symptomatic Disease Detection Using RGB Imaging

Early AI-driven disease detection research primarily focused on identifying diseases after visible symptoms had appeared, using RGB imagery and DL-based computer vision models. Initial studies established the feasibility of post-symptomatic recognition under controlled conditions. For example, Gao et al. [124] investigated the detection of anthracnose, early blight, and late blight in potato plants using RGB images.

Subsequent work expanded RGB-based disease detection to a broader range of crops and pathogens. Liu et al. [123] addressed multiple grape diseases, including anthracnose, white rot, gray mold, and powdery mildew, using a fusion-based YOLO framework. Similarly, YOLO-based pipelines were applied to cucumber crops by Ding et al. [122] and Xie et al. [125], enabling the detection of multiple diseases under varying illumination conditions and in the presence of mixed infections.

As RGB-based disease detection matured, later studies increasingly emphasized robustness and discrimination among visually similar disease classes. Wang and Liu [126] proposed the integration of multi-scale feature fusion and attention mechanisms for tomato disease detection, improving differentiation between diseases with overlapping visual symptoms.

While RGB-based approaches have demonstrated strong performance once symptoms are visible, their inherent reliance on visual cues limits their effectiveness for early-stage detection, motivating the exploration of sensing modalities capable of identifying disease prior to symptom manifestation.

### 3.3.2. Pre-Symptomatic Disease Detection Using Spectral Imaging

A key conceptual advance in AI-based disease detection is the transition from post-symptomatic recognition to pre-symptomatic identification, where infection-induced physiological changes precede visible symptoms. Spectral imaging modalities, including multi-spectral and hyperspectral sensing, enable the capture of subtle biochemical and structural variations associated with early disease development.

Giakoumoglou et al. [19] demonstrated that multispectral imaging combined with DL could detect *Botrytis cinerea* infection in cucumber plants prior to visible symptom onset. Building on this work, Giakoumoglou et al. [20] employed instance segmentation to localize early-stage infections more precisely.

Further contributions explored the integration of spectral and RGB information for early disease detection. Kapetas et al. [45] performed early detection of gray mold in tomato plants using multispectral imagery, instance segmentation, and descriptor-based classification. Extending this line of research, Kapetas et al. [46] investigated *Botrytis cinerea* infection in pepper plants, leveraging vegetation indices derived from multispectral data to enhance early-stage disease discrimination.

Spectral imaging can be useful for detecting *Botrytis cinerea* infections prior to visual appearance, depending upon band selection and the choice of vegetation index. Research has found that a portion of the red-edge spectral range (700–740 nm) is sensitive to changes in chlorophyll content due to fungal infection. This region also represents photosystem II

efficiency; therefore it may provide an earlier indication of *B. cinerea* presence than other regions [19,20]. Changes in the near-infrared spectral region (750–900 nm) are associated with loss of cell structural integrity. Researchers have indicated that significant changes occur within this range once hyphae penetrate into mesophyll tissue. The short-wave infrared spectral region (1400–1900 nm) provides information related to leaf water content. Researchers have demonstrated that biotic stress caused by pathogens disrupts water transport through leaves. Therefore, researchers have determined that biotic-stress-induced changes in leaf water content can be measured in the SWIR spectral range 1–3 days prior to visual symptoms [42,43]. Researchers have used various vegetation indices (VIs) including NDRE, PRI, and SIPI to detect early biotic stress (EBS). Researchers have reported that these VIs show greater sensitivity to EBS than NDVI [42]. However, researchers note that the spectral signatures for EBS may overlap with spectral signatures for nitrogen deficiency (red-edge shift), drought (water bands in the SWIR), and iron deficiency (visible chlorosis bands). Therefore, single-index thresholding is not sufficient to detect EBS. To improve discrimination ability among various crop stresses, researchers recommend using multi-band DL classifiers trained on the full spectral profile [20,45,46].

In contrast to pest detection, which often relies on population-level monitoring, disease detection is intrinsically linked to the temporal evolution of infection, spanning latent physiological changes through to visible symptom expression. Consequently, AI-based disease detection methods can be viewed as progressing from post-symptomatic visual recognition toward increasingly early, pre-symptomatic identification enabled by advanced spectral sensing and data-driven analysis.

A number of practical aspects of model selection stand out from the results shown in Tables 2 and 3. Architecture-wise, the majority of models developed for use with the AI-based methods of detecting pests have been based upon YOLO, which provides both real-time inference and excellent object localization capabilities; among all variants of YOLO, YOLOv8 has been by far the most commonly utilized. Performance, however, can vary significantly depending on context: mAP50 values in field conditions were reported to be 70.2% (*Tuta absoluta*) [120], while multi-insect open-field experiments found mAP50 values to be 99.5% [116] on what appear to be very similar detection tasks. These values clearly indicate that variations in environmental conditions, along with those associated with the quality of available data, affect performance much more than does architecture itself. In cases where visual appearance of diseases is relatively indistinguishable, attention-based and/or transformer-based detectors generally perform better than do standard YOLO detectors at greater computational cost. For pre-symptomatic detection using spectral imaging techniques, there is no current alternative to the use of U-Net++ or some form of transformer-based segmentation. This is because standard RGB-based models lack the required spectral sensitivity to detect subtle sub-threshold physiological changes. The majority of the research cited utilizes data acquired from tomatoes, but the degree to which such models may be applicable to other crops is entirely unknown. Practically speaking, acquiring high-quality crop-specific training data is much more important than selecting an optimal architecture for application within this area.

#### 4. Challenges, Limitations, and Discussion

AI-based plant health monitoring has a number of significant technical, practical, and socio-economic limitations which have limited its ability to be widely adopted by farmers. For this reason it will be useful to understand the current limitations of AI as an aid to plant health monitoring when assessing reports on the performance of models, or forming a view about how much AI can help in real farm environments.

#### 4.1. Fundamental Methodological Challenges

**Dataset scarcity and class imbalance** present pervasive challenges for AI model development. Many plant diseases and pest infestations occur sporadically or seasonally, making systematic data collection challenging and time-intensive [34]. Rare diseases, emerging pathogens, and region-specific crop varieties particularly suffer from limited available training data, with some conditions represented by mere dozens of examples insufficient for DL [38]. Class imbalance causes models to develop bias toward healthy plants, resulting in poor detection sensitivity for diseased specimens that represent the most agriculturally critical cases [62]. The annotation costs further compound these challenges, as creating high-quality training datasets demands expert botanical and phytopathological knowledge for accurate disease identification, particularly for distinguishing between visually similar conditions or identifying early-stage infections [10]. One way to reduce annotation costs is active learning, where a model iteratively selects the most informative unlabeled samples for expert annotation, lowering the total labeling effort needed. This is useful in agricultural settings where expert annotation is slow and costly; uncertainty-based and core-set selection strategies have been shown to cut labeling effort by 60–80% in comparable biological imaging tasks. Semi-supervised learning, which uses large amounts of unlabeled field imagery alongside a small labeled set, is a complementary option, with methods such as FixMatch and MeanTeacher showing good results in low-label settings relevant to plant disease classification. A related issue is the choice of evaluation metrics. Most studies in Tables 2 and 3 report mAP50 or accuracy as the main metric. On imbalanced agricultural datasets, where diseased samples are far fewer than healthy ones, accuracy is misleading: a model that always predicts healthy can exceed 90% accuracy on a dataset with 10% disease prevalence while being entirely useless. The Precision-Recall curve, F1-score, and Matthews Correlation Coefficient (MCC) are more suitable for imbalanced settings. The reviewed literature also rarely reports performance specifically for early-stage or pre-symptomatic infections, which is the most important operating point for crop protection. Future evaluations should include per-class performance at each infection stage to allow meaningful comparisons of early versus late-stage sensitivity. A well-known limitation of DL models is that they need large amounts of annotated training data to perform reliably, which is a persistent bottleneck in agricultural AI [40]. Unlike traditional diagnostic approaches that draw on accumulated expert knowledge, AI systems learn entirely from labeled examples, requiring thousands to millions of annotated images for disease and pest detection [58]. This is particularly problematic for rare diseases, emerging pathogens, and region-specific crop varieties with few available examples. The problem is worse for early-stage detection, where subtle pre-symptomatic changes require datasets covering the full range of infection progression under varied conditions [16]. Transfer learning, data augmentation, and generative AI methods that synthesize disease images partially address this [128], but the need for high-quality, expert-annotated datasets remains a hard constraint.

AI's ability to identify statistical correlations does not establish causal relationships between variables. Using AI in trap-based systems for monitoring *Tuta absoluta* has provided good results for detecting adult insects and predicting population trends. However, it is impossible to measure the egg-laying process (the most important aspect of determining how much of the crop will be damaged) [111,113]. Since the model was trained on trap counts, environmental factors, and population dynamics, there is no mechanism for understanding biological reproduction processes or the timing of larvae [111]. This contrasts with traditional entomological models, which are built on causal knowledge of pest lifecycle biology [37].

Similarly, AI used for pre-symptomatic disease detection can provide a spectral signature related to infection prior to the appearance of clinical symptoms. Nonetheless, the physiological changes identified by the model (i.e., changed chlorophyll fluorescence, temperature changes, etc.) do not directly indicate whether or not an infectious agent exists, nor whether different infectious agents producing equivalent spectral signals exist [16]. Therefore, molecular diagnostic techniques are required to verify the presence of a specific pathogen.

Because of its correlation-based characteristics, AI should act as a supplement to traditional diagnostic techniques rather than replace them. Traditional diagnostic techniques include molecular methods (PCR and ELISA), which can confirm the presence of a pathogen by identifying DNA/RNA sequences or pathogen proteins that are unique to a given organism [35,36]. An effective method to integrate AI into this type of diagnostic pipeline is to utilize AI for initial screening of a large area to identify suspicious plants. Once identified, the AI results can be confirmed via molecular diagnostic tests. This provides significant cost and time savings over utilizing molecular diagnostic tests uniformly across all plants sampled [65]. For example, an AI system capable of hyperspectral analysis can analyze an entire field and quickly identify spectral anomalies indicative of potential disease or pest presence [20], with subsequent PCR tests only being conducted on the anomalous plants. By limiting unnecessary treatment applications while still catching actual infections in time, this approach provides a better overall economic and ecological outcome.

One major problem in developing AI-based systems is distinguishing biotic stresses (pathogens and pests) from abiotic stresses (drought, nutrient deficiencies, temperature extremes). Many times the symptoms produced by both biotic and abiotic stresses are identical (e.g., yellowing leaves can be caused by lack of nitrogen, viral infection, root disease, or water stress; necrotic lesions can result from bacterial or fungal pathogens, salt damage, or herbicides) [6,80]. As previously stated, RGB imaging alone cannot effectively separate the two types of stresses because they exhibit similar phenotypically expressed symptoms (chlorosis, wilting, necrosis, stunted growth) [16]. Hyperspectral imaging can potentially assist in separating the two types of stresses. Biotic stresses tend to present non-uniform spatial distribution patterns and contain biochemical signatures unique to each pathogen. Abiotic stresses are typically uniform in space and correlate with physical gradients in the environment [42]. Although hyperspectral imaging provides superior capability to detect differences between biotic and abiotic stresses, when plants experience both types of stresses simultaneously the resulting symptom pattern exhibits complexity and is generally not represented within training datasets collected during exposure to a single stress condition [7].

To overcome these challenges it will be essential to develop large, annotated data collections representing many different crops, disease types, pest species, growth stages, and environmental conditions. These datasets will enable researchers to train foundational models (large-scale AI architectures that capture broad patterns relating to plant health), in analogy with language models like GPT [129] learning about language patterns, or DINO [130,131] learning about visual representations. These foundational models will enable widespread application across multiple crops, diseases, and geographic locations requiring limited amounts of new labeled data, enabling faster response times to newly discovered threats and increased accessibility to sophisticated AI capabilities [132]. The creation of such large datasets will require cooperative efforts among research institutions, agricultural extension services, and farmers, with common data collection protocols and data quality standards.

#### 4.2. Technical and Operational Challenges

**Domain specificity and model generalizability** represent critical limitations constraining practical deployment. AI models trained on data from specific geographical locations, growth environments, or imaging conditions frequently exhibit poor generalization when deployed in different contexts [106]. Models developed using laboratory or greenhouse imagery often fail when applied to field conditions due to distribution shifts in background clutter, lighting variability, and plant appearance [133]. Regional crop variety differences exacerbate these challenges, as different cultivars exhibit substantial morphological variation affecting disease symptom presentation and AI model performance [38]. Leaf shape, color, texture, and size vary across varieties, requiring models to distinguish disease-induced changes from natural cultivar characteristics, while disease resistance breeding creates additional complexity as resistant varieties may show minimal or atypical symptoms [4]. Overfitting to specific environments or datasets remains a persistent problem, with models learning spurious correlations between irrelevant features and disease presence rather than genuine diagnostic patterns. This manifests particularly severely for hyperspectral and multispectral imaging systems, where sensor calibration drift, atmospheric conditions, and sun angle variations substantially affect spectral signatures [42].

**Field condition variability** presents extreme challenges for AI deployment in real-world agricultural environments. Natural lighting variations throughout the day create shadows, specular highlights, and color temperature shifts that alter plant appearance and confound disease detection algorithms trained on uniformly illuminated imagery [16]. Weather conditions directly impact sensor performance, cloud cover transitions produce rapid illumination changes during field deployment, while morning dew and precipitation create moisture artifacts on leaves that may be misinterpreted as disease symptoms or obscure genuine infection indicators [86]. Occlusion challenges compound these difficulties, as dense crop canopies create severe visibility limitations with overlapping leaves obscuring disease symptoms and limiting AI system ability to assess interior plant health [16].

#### 4.3. Socioeconomic and Adoption Barriers

Beyond technical constraints, substantial **socioeconomic and practical barriers** impede widespread AI adoption in agriculture. Advanced AI systems require infrastructure investment—specialized sensors, computing hardware, reliable internet connectivity—that remains prohibitively expensive for smallholder farmers who produce significant portions of global food supply but operate under severe resource constraints [38]. Farmer trust and model interpretability present additional adoption challenges, as most DL models function as “black boxes” providing predictions without intelligible explanations [41]. Farmers accustomed to visual symptom assessment and decades of experiential knowledge may hesitate to implement management actions based on opaque AI recommendations, particularly when suggestions conflict with traditional practices or local knowledge [38]. The lack of interpretability complicates validation and error diagnosis, as stakeholders cannot easily assess whether incorrect predictions result from genuine edge cases, model limitations, or data quality issues [65].

In order to address some of the inequitable differences in cost across various types of sensors, there is a growing body of literature discussing how to make remote sensing technology accessible for developing regions and rural communities. Hyperspectral cameras used on drones come at a price of \$15,000 to over \$100,000 per unit; most small-scale farmers, who farm approximately 84% of all farmland, cannot afford such units. The price range of multispectral units (\$3000–\$8000) is equally unaffordable. Therefore, it will be necessary to compare the performance benefits associated with the use of hyperspectral units for early detection against their costs when evaluating their contribution to food security.

For example, a model achieving 95% pre-symptomatic accuracy using a hyperspectral camera costing \$50,000 could potentially contribute less to food security than a model achieving 80% post-symptomatic accuracy using a \$500 smartphone. Thus, the relative trade-offs in terms of cost and benefit that occur with the use of various sensing technologies should play a role in determining research priorities and point toward the lower-cost options for spectral sensing discussed in Section 5.

Although there are several factors that limit the applicability of AI as an independent method for identifying plant health issues, AI is still being utilized to assist in addressing several major challenges facing agriculture today, including climate change impacts, emerging pests and diseases, and support for more sustainable production methods [1]. However, it is essential to treat AI as a monitoring and screening tool within the context of a comprehensive management strategy rather than as an independent diagnostic device. When combined with agronomic knowledge, molecular diagnostics, and environmental monitoring, AI can help shift disease management away from purely reactive responses toward earlier interventions before the window closes for treatments to remain effective [21]. The combined utilization of AI as part of an integrated approach supports precision agriculture, with reported potential to reduce pesticide usage by 40–60% while maintaining levels of crop protection [51].

## 5. Future Directions

The rapid evolution of AI technologies presents unprecedented opportunities to address fundamental limitations in current plant health monitoring systems while establishing new paradigms for proactive agricultural management. Future developments must focus on the following critical areas that collectively address technical constraints, practical deployment challenges, and societal considerations essential for widespread adoption.

**Multimodal AI fusion** represents the next critical advancement in plant health monitoring, integrating various modalities, e.g., RGB imaging, hyperspectral imaging, thermal sensing, and 3D structural analysis into unified diagnostic frameworks. This sensor fusion approach overcomes individual modality limitations by capturing biochemical changes, stress-induced temperature variations, and morphological alterations simultaneously, enabling comprehensive plant health assessment before visible symptoms appear. Recent advances in hyperspectral-based DL demonstrate the potential for detecting *Botrytis cinerea* infections as early as the first day, enabling intervention before significant crop damage occurs [20].

**Generative AI (GenAI) for synthetic data augmentation** addresses the critical bottleneck of limited annotated training datasets that constrains current AI model development [134]. Generative Adversarial Networks (GANs) [135] and diffusion models [136,137] can create realistic synthetic images of plant diseases and pest infestations across diverse growth stages, environmental conditions, and symptom severities. This approach enables robust model training for rare diseases or emerging threats where real-world data is scarce, particularly valuable for developing AI systems capable of detecting invasive species or climate-induced pathogen variants before widespread agricultural impact. Recent advances demonstrate the potential of GANs for generating diverse plant disease imagery that significantly improves model generalization [128].

**Explainable AI (XAI)** emerges as essential for building farmer trust and enabling practical adoption of AI technologies in agricultural decision-making. Current DL models function as “black boxes”, undermining farmer confidence and regulatory acceptance. Most current XAI methods produce saliency maps or class activation maps (CAMs) that highlight which image regions influenced the prediction. While useful, these fall short of the agronomic explanations practitioners need. A heatmap on a leaf region does not tell a

farmer whether the signal corresponds to powdery mildew, nitrogen deficiency, or herbicide damage, all of which can produce similar visual and spectral patterns. A more useful output would be something like: “early *Botrytis cinerea* infection detected based on reflectance drop in the 700–740 nm red-edge band and increased fluorescence, a pattern inconsistent with nitrogen deficiency, which affects the 670 nm absorption peak without the fluorescence change.” Producing such explanations requires models whose internal features correspond to physiologically interpretable quantities, which can be approached through concept bottleneck models, prototype-based classifiers, or auxiliary training on spectral index annotations. Moving from pixel-level attribution to feature-level explanations grounded in phytopathology would make XAI a more practical decision-support tool for farmers and agronomists. Advanced approaches such as trainable attention mechanisms offer promising solutions for making both convolutional networks and vision transformers more interpretable in agricultural contexts [138].

**Edge AI for real-time processing** will revolutionize field deployment by enabling autonomous decision-making without cloud connectivity dependencies. Edge computing devices equipped with specialized AI accelerators will process sensor data locally on tractors, drones, and field robots, reducing latency from minutes to milliseconds while maintaining data privacy and enabling operation in remote areas. This technological shift supports precision interventions such as real-time pesticide application guided by immediate AI analysis, improving treatment efficacy while minimizing chemical usage. Emerging citizen science tools demonstrate the feasibility of energy-autonomous embedded systems integrating environmental sensors with hyperspectral imaging for distributed agricultural monitoring [48]. A practical middle ground between full hyperspectral systems and standard RGB cameras is emerging in the form of low-cost spectral sensors and smartphone-based multimodal systems. Compact sensors covering 8–16 bands in the visible and near-infrared are now available for under \$1000. Smartphone-based RGB-thermal fusion is another option: consumer thermal cameras that attach to smartphones (\$200–\$500) can detect stomatal closure and transpiration anomalies that precede visible symptoms, while the RGB channel provides structural context. With on-device DL inference, such systems could offer useful pre-symptomatic screening at a fraction of the cost of dedicated hyperspectral hardware, provided models are trained on data from these lower-cost sensors.

**Data privacy and farmer adoption** concerns center on ownership and control of agricultural data, particularly when AI systems require cloud-based processing or data sharing for model improvement. Future frameworks must address farmer concerns about data sovereignty while enabling collaborative data collection necessary for robust AI development. The digital divide between large commercial operations and smallholder farmers threatens to exacerbate agricultural inequalities, necessitating development of low-cost, accessible AI solutions operating on smartphones or simple hardware platforms. Innovative approaches using distributed ledger technology offer promising solutions for AI data model verification while maintaining farmer data privacy and control [139].

**Regulatory frameworks for AI in agriculture** remain largely undeveloped, creating uncertainty about liability, safety standards, and approval processes for AI-driven pest management decisions. Future policy development must balance innovation encouragement with risk management, establishing clear guidelines for AI validation, performance monitoring, and accountability in agricultural applications. Standardized testing protocols and certification processes will be essential for ensuring reliable AI deployment while maintaining farmer and consumer confidence.

**Foundational Models (FM) for agriculture**, analogous to large language models like GPT [129] or computer vision models like DINOv2 [130] and DINOv3 [131], are capable of performing multiple agricultural tasks through unified architectures trained on mas-

sive, diverse datasets. These agricultural FMs would integrate plant health monitoring, growth prediction, yield estimation, and environmental stress detection into single systems adaptable to new crops, regions, and challenges through fine-tuning rather than complete retraining. A practical limitation of applying current FMs to agriculture is the mismatch between their general-purpose pretraining data and the agricultural visual domain. DINOv2, pretrained on the LVD-142M internet-scale image collection, may not capture domain-specific features relevant to plant health, such as fine lesion textures, spectral band patterns in multispectral imagery, or crop canopy geometry. There is also a large computational gap: a ViT-B/14 backbone has around 86 million parameters and requires substantial GPU memory, making real-time edge inference on current field hardware impractical, whereas YOLOv8-nano has around 3.2 million parameters and runs in real time on embedded systems below 5 W. In the near term, FMs are more suited as offline pretraining backbones whose representations are then distilled into lightweight task-specific models for deployment. Pretraining FMs on large collections of unlabeled plant imagery covering diverse crops, imaging conditions, growth stages, and spectral modalities would likely give better initialization than fine-tuning general-purpose models. Self-supervised pretraining on agricultural data [132] is a more practical path toward agricultural FMs than large-scale supervised training.

**Cross-domain validation and model generalization** represents a critical challenge that must be addressed to ensure AI systems perform reliably across diverse agricultural environments, crop varieties, and imaging platforms. Current AI models often suffer from domain shift problems, where systems trained on specific datasets fail to maintain performance when deployed in different geographical regions, weather conditions, or with alternative sensing equipment [140]. Future research must prioritize developing robust validation frameworks that systematically test model performance across multiple domains, including variations in lighting conditions, soil types, cultivar differences, and camera specifications. Adversarial domain adaptation methods such as Domain-Adversarial Neural Networks (DANNs) address this by training feature extractors to be invariant to domain shift, using a gradient reversal layer that penalizes domain-discriminative features and produces representations that transfer across imaging conditions and locations. Domain generalization methods, which target unseen domains without access to target-domain data during training, include meta-learning approaches and augmentation strategies that simulate domain shifts such as illumination changes, sensor noise, and viewpoint variation. Future benchmarks should require cross-domain evaluation as standard.

**Dimensionality reduction and band selection for hyperspectral systems** will be a key area in making spectral AI more practical. The large amounts of high-dimensional data generated from hyperspectral sensing (data cubes) require significant computational power to process. In addition, these types of data can be challenging to analyze due to low sample-to-feature ratios; therefore, there exists a high degree of statistical difficulty when working with hyperspectral images using DL, and DL algorithms carry a high risk of overfitting. This issue is partially addressed through the use of techniques such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and other similar dimensionality reduction methods. However, if non-linear relationships exist between the spectral properties related to specific diseases, these methods will fail to identify them. An alternative to manually selecting bands based on knowledge of how different diseases manifest spectrally is autoencoder-based learning. Autoencoders learn compact representations of hyperspectral image data that preserve physiologically meaningful spectral variability. The ability of AI to perform band selection will therefore provide an additional means of reducing costs and improving deployment speed. Specifically, if a three- to five-band multispectral camera could provide the same level of diagnostic accuracy as

a 200-band hyperspectral imaging system, deployment costs would drop by one to two orders of magnitude, directly addressing the accessibility problem discussed in Section 4.3.

**Cost-sensitive evaluation and early-stage metrics.** Many standard benchmarks used today treat false negatives and false positives similarly. While this may seem reasonable when evaluating general computer vision systems, it is far less reasonable when evaluating systems intended for disease detection. A false negative means a genuine infection goes undetected, which can lead to full crop loss, while a false positive at worst triggers an unnecessary treatment. Future benchmarks should reflect this asymmetry through cost-sensitive evaluation, assigning higher penalties to missed detections at early infection stages. Evaluation protocols should also report sensitivity separately at each infection stage, i.e., pre-symptomatic, early symptomatic, and late symptomatic. We suggest that sensitivity at the pre-symptomatic stage be adopted as a primary reported metric alongside overall mAP in future studies.

## 6. Conclusions

This review has examined the transformative potential of AI for plant health management, emphasizing the critical paradigm shift from reactive symptom-based detection to proactive, pre-symptomatic intervention strategies. AI technologies, particularly DL approaches leveraging computer vision and advanced sensing modalities, demonstrate unprecedented capabilities for rapid, scalable, and increasingly accurate detection of plant diseases and pest infestations across diverse agricultural contexts. Recent breakthroughs in hyperspectral imaging combined with deep neural networks enable detection of pathogen infections days before visible symptom manifestation, opening intervention windows that can prevent substantial crop losses while dramatically reducing reliance on prophylactic pesticide applications.

However, successful agricultural AI deployment requires clear-eyed assessment of fundamental limitations alongside technological capabilities. Current systems remain constrained by substantial data requirements, challenges in distinguishing correlation from causation, difficulties differentiating between biotic and abiotic stress factors, and generalization problems when deployed across diverse environmental conditions and crop varieties. These limitations position AI not as a replacement for traditional diagnostic methods and agronomic expertise, but as a powerful *complementary* tool within integrated plant health management frameworks. The combination of AI-enabled rapid screening across large areas with targeted application of molecular diagnostics for confirmation, supported by agronomic knowledge and environmental monitoring, offers the most promising pathway toward sustainable, effective crop protection.

Looking forward, the convergence of multimodal sensing, explainable AI frameworks, edge computing capabilities, and emerging foundational model architectures promises to address many current limitations while dramatically expanding AI capabilities in agricultural applications. The development of comprehensive, globally representative agricultural datasets supporting foundational model training stands as a prerequisite for democratizing advanced AI capabilities, enabling rapid response to emerging threats, and ensuring technology benefits accrue equitably across diverse farming communities rather than exacerbating existing agricultural inequalities.

Ultimately, AI represents an indispensable enabling technology for addressing contemporary agricultural challenges—climate change impacts, emerging pests and diseases, environmental sustainability imperatives, and the fundamental need to feed growing populations with reduced resource inputs. By embracing AI as a powerful tool within integrated, knowledge-based agricultural systems rather than a standalone solution, the global agricultural community can work toward the ultimate goal of proactive plant health man-

agement: preventing crop losses before they occur while building resilient, sustainable food production systems capable of meeting 21st-century challenges.

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