International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 • Website: www.ijfmr.com • Email: editor@ijfmr.com

Advancements in Plant Disease Detection: A Comprehensive Review of Traditional, Modern, and AI-Driven Approaches

Mr. Mayank Tyagi

MBA (Ai & Ml), Maa Shakumbhari University Saharanpur

Abstract
This paper provides a comprehensive review of advancements in plant disease detection, moving from traditional to modern and AI-driven approaches. It highlights that traditional methods, such as visual inspection, microbiological isolation, culturing, and molecular and serological techniques, are often limited by being time-consuming, subjective, or requiring specialized expertise and lab processing. These limitations can lead to significant crop yield losses, economic setbacks, and threats to food security.
The review then discusses modern, non-destructive sensor technologies, which are crucial for detecting diseases in their early stages, often before visible symptoms appear. These technologies include:

- Hyperspectral Imaging (HSI): Captures detailed "spectral fingerprints" of plants to detect subtle physiological changes.
- Multispectral Imaging (MSI): Uses a limited number of spectral bands, often including near-infrared (NIR), to identify abnormal plant conditions more cost-effectively than HSI.
- Thermal Imaging: Detects temperature fluctuations in plants caused by physiological changes during infection.
- Chlorophyll Fluorescence Imaging (CFI): A non-invasive technique that detects early stress responses by analyzing chlorophyll emissions.
- LiDAR and Drones: Used for aerial analysis of crop health, enabling early diagnosis and monitoring of large agricultural areas.

Finally, the paper details how Artificial Intelligence (AI) and Deep Learning (DL) have revolutionized this field through automated, highly accurate diagnostic capabilities. The document covers various deep learning architectures, including Convolutional Neural Networks (CNNs) like AlexNet, VGG, ResNet, and YOLO, which are used for image classification, feature extraction, and real-time disease localization. It also mentions the use of semantic segmentation models like U-Net for pixel-level disease mapping, and the role of transfer learning and explainable AI (XAI) in improving model performance and transparency. The review concludes with an emerging paradigm of federated learning for decentralized, privacy-preserving model training.

1. Introduction

The health of global agriculture is inextricably linked to effective plant disease management. Early and accurate detection and diagnosis of plant diseases are paramount for efficient plant production, leading to a substantial reduction in both qualitative and quantitative crop yield losses. This proactive approach is critical for mitigating the most significant challenge in crop production, which can otherwise result in considerable economic setbacks.

The escalating global population, projected to reach 9.3 billion by 2050, necessitates a 50% increase in food production to meet demand. However, plant pathogens and pests currently cause up to 40% yield losses in major staple crops such as maize, rice, and wheat, translating to an astonishing annual worldwide economic loss of approximately US$220 billion. Specific analyses indicate estimated yield losses of 21.5% for wheat, 30.3% for rice, and 22.6% for maize. Beyond direct yield impacts, plant health is intrinsically tied to environmental sustainability and overall economic stability. Compromised plant health can trigger reduced yields, inflated production costs for farmers, higher food prices for consumers, and even food shortages, creating cascading negative effects on the broader economy. The transboundary movement of plants and plant products also risks introducing invasive pests and diseases, further disrupting trade and causing economic losses. Neglecting plant health has long-term consequences, including biodiversity loss, ecosystem degradation, and environmental imbalances. Emerging plant diseases pose persistent threats, particularly devastating in limited-resource countries where they exacerbate existing challenges in crop production. The increasing influence of climate change, affecting temperature, atmospheric CO2 concentration, and water availability, is a primary concern for plant pathologists, as it directly impacts plant, pathogen, and disease development. This environmental shift contributes to pathogen and vector expansion, as well as the emergence and re-emergence of endemic diseases.

The profound economic losses and direct threat to global food security underscore that plant disease detection is not merely an agricultural optimization problem. It stands as a fundamental component of global stability, public health (considering the potential for mycotoxins to affect food safety), and poverty alleviation. This elevates the field's importance from a technical challenge to a societal imperative, highlighting research and development in this area as critical investments in global resilience and human well-being. Furthermore, the identification of climate change as a critical factor influencing plant, pathogen, and disease development indicates that the problem of plant disease is dynamic and likely intensifying. This suggests that future plant disease detection systems must integrate climate data and predictive odelling to anticipate and adapt to evolving disease patterns, necessitating a more holistic, interdisciplinary approach combining advanced sensing with environmental science and predictive analytics.

Historically, plant disease diagnosis relied heavily on traditional methods such as visual inspection by farmers and agricultural experts. This involved identifying characteristic plant disease symptoms like lesions, blight, galls, or wilts, or visible signs of pathogens such as mycelium or spores. Microbiological methods, involving pathogen isolation on selective, artificial media, and molecular and serological methods, have also been employed by plant protection services and in research and industrial development. The devastating impact of historical neglect of plant health, exemplified by the Irish Potato Famine in the mid-19th century due to widespread potato late blight, underscores the critical need for effective detection. The historical reliance on time-consuming, expertise-dependent, and resource-intensive methods, as evidenced by farmers' persistent visual examinations , presents inherent limitations. The subsequent emergence of automated and semi-automated systems that are faster, more accurate, and less expensive signifies a fundamental shift. This progression represents a move from human-centric, subjective, and often delayed diagnostic processes to machine-driven, objective, and rapid detection, driven by the necessity to overcome the inefficiencies and limitations of traditional approaches for more effective agricultural protection.

2. Traditional Approaches to Plant Disease Detection

This section delves into the established methods of plant disease detection, detailing their mechanisms and critically evaluating their inherent strengths and, more importantly, their limitations, setting the stage for the necessity of modern advancements.

Visual Inspection and Symptom-Based Diagnosis

Visual inspection is a foundational technique in plant disease diagnosis, relying on careful observation of physical characteristics to identify symptoms of disease, pest damage, or nutrient deficiencies. Farmers, agricultural practitioners, and plant pathologists traditionally identify diseases based on characteristic plant disease symptoms such as leaf spots, blights, stem cankers, root rot, or abnormal growth patterns like stunting or distortion. They also look for visible signs of a pathogen, such as uredinospores or mycelium. This method is crucial for early detection by allowing growers to observe physical symptoms like discoloration or wilting, signaling potential issues for timely management. It provides immediate feedback without complex laboratory tests.

Despite its immediacy, visual inspection is inherently subjective and may not always be accurate, especially for diseases with similar symptoms or those exhibiting inconspicuous signs. It is time-consuming and labor-intensive, particularly in large fields, and prone to human error, leading to delayed interventions. In the worst-case scenario, an undetected infection can cause an entire crop to decline, severely impacting yield. While visual inspection holds historical significance and remains a preliminary diagnostic step, its inherent flaws in scalability, objectivity, and sensitivity to early symptoms render it insufficient as a primary method for modern agricultural demands. This clearly demonstrates the urgent need for automated, objective, and more sensitive detection technologies.

Microbiological Methods: Isolation and Culturing

These methods involve the isolation of pathogens on selective, artificial media, followed by culturing to grow and identify the causative agent. The process typically includes collecting infected plant tissue, surface-sterilizing it to remove contaminants, plating the tissue on a nutrient medium (e.g., agar), incubating the plates to allow pathogen growth, and finally identifying the pathogen based on its morphology and growth characteristics. These conventional techniques are employed by plant protection services and in both research and industrial development for pathogen identification.

While capable of confirming specific pathogens, isolation and culturing are time-consuming and labor-intensive, requiring specialized laboratory expertise and resources. Their slow turnaround time limits their utility for rapid, field-scale interventions, often delaying necessary actions. These methods offer definitive pathogen identification, indicating high accuracy. However, their slow nature and reliance on expert labor limit their practicality for rapid, widespread disease management, especially in large-scale agricultural settings. This highlights a critical trade-off, where precision comes at the cost of speed and accessibility.

Molecular and Serological Techniques

Molecular and serological methods are readily applied for the diagnosis and detection of plant pathogens, used by plant protection services and in research and industrial development. Serological tests are based on the specific reaction of antibodies with antigens. A wide range of formats exists for detecting plant viruses, including traditional methods like tube precipitin and gel diffusion, and more modern techniques such as Enzyme-Linked Immunosorbent Assay (ELISA). ELISA is highly economical in antiserum use, adaptable for large-scale testing, and enables quantitative measurement. Simpler, on-site methods like dot immunobinding assay (DIBA), tissue blotting immunoassay (TBIA), and lateral flow assay (LFA) or dip stick assay are also available, with LFA being particularly notable for its quick, lab-independent, and userfriendly nature.

Real-time Polymerase Chain Reaction (qPCR) is currently considered the “gold standard” method for detecting plant pathogens. This technique amplifies and simultaneously quantifies targeted DNA molecules by monitoring a fluorescent signal that increases proportionally to the number of amplicons. qPCR allows for accurate, reliable, and high-throughput quantification of pathogen DNA in various environmental samples, including host tissues, soil, water, and air. These molecular diagnostic tests offer significant advantages over conventional methods, including the ability to detect organisms without prior culturing, faster turn-around times, potential for high-throughput analysis, and the capacity to identify pathogen species or strains, including fungicide resistance alleles. The designation of qPCR as the “gold standard” due to its accuracy, reliability, and quantification capabilities, alongside ELISA’s scalability and LFA’s on-site application, establishes a high performance benchmark. These methods represent a clear progression towards more precise and efficient laboratory-based diagnostic tools. However, they still typically require sample collection and laboratory processing, which can be a bottleneck for true real-time, large-scale field application. The ultimate goal for advanced sensor and AI methods is to achieve comparable diagnostic power and specificity *in situ* or remotely, thereby complementing and extending the reach of these lab-based approaches.

Inherent Limitations and Challenges of Conventional Methods

Traditional plant disease detection methods, including visual inspection and laboratory-based techniques, are consistently characterized by their time-consuming nature, reliance on specialized expertise, and high resource intensity. Visual inspection suffers from subjectivity and variability, often failing to accurately diagnose diseases, especially those with similar or inconspicuous symptoms. This can lead to undetected infections that cause an entire crop to decline, severely impacting yield. Microbiological isolation and culturing, while accurate, are labor-intensive and time-consuming, requiring significant expertise and specialized facilities. Overall, these methods exhibit limitations in sensitivity and specificity compared to modern techniques. Furthermore, if not applied in the early stages of pathogenesis, traditional techniques are often ineffective in restricting and managing disease spread.

The collective shortcomings of traditional methods, which lead to significant economic losses , inefficiencies , and delayed interventions , pose a direct threat to food security and farm profitability. The inability to detect diseases at their earliest stages or when symptoms are inconspicuous represents a critical failure point, potentially resulting in widespread crop loss. This is not merely a matter of convenience but a severe constraint on agricultural sustainability. The development and adoption of modern, automated detection techniques are thus a crucial strategic response to these economic and food security implications, providing a compelling justification for continued investment in AI and sensor-based systems.

Table 1: Comparison of Traditional Plant Disease Detection Methods

Method Name	Principle/Mechanism	Key Advantages	Key Limitations	Relevant Sources
Visual Inspection	Symptom observation (e.g., lesions, discoloration)	Low cost, immediate feedback, no specialized equipment	Subjective, variable accuracy, time-consuming, labor-intensive, expertise-dependent, misses early/inconspicuous symptoms, prone to human	

Method Name	Principle/Mechanism	Key Advantages	Key Limitations	Relevant Sources
			error, poor scalability	
Microbiological (Isolation & Culturing)	Pathogen growth on selective media	Confirms pathogen identity, can isolate specific strains	Time-consuming, labor-intensive, requires specialized laboratory expertise and facilities, slow turnaround time, limited for rapid field-scale interventions	
Serological (e.g., ELISA, LFA)	Antibody-antigen reaction	Adaptable for large-scale testing, economical, quantitative, on-site (LFA)	Requires specific antibodies, may not detect all pathogens, can be less sensitive than molecular methods, LFA suitable for high-concentration pathogens	
Molecular (e.g., PCR, qPCR)	DNA/RNA amplification and quantification	High accuracy, high sensitivity, high-throughput, faster turnaround, quantifies pathogen load, identifies species/strains, detects fungicide resistance alleles	Requires specialized equipment and expertise, initial setup cost, sample collection and lab processing still a bottleneck for true real-time field use	

3. Advanced Sensor-Based Technologies for Early Detection

This section explores the cutting-edge non-destructive sensor technologies that have revolutionized plant disease detection, detailing their operational principles, data analysis techniques, and diverse applications in modern agriculture.

Overview of Non-Destructive Optical Sensing Techniques

Optical techniques, including RGB imaging, multi- and hyperspectral sensors, thermography, and chlorophyll fluorescence, have demonstrated significant potential in developing automated, objective, and reproducible detection systems. These systems are crucial for the identification and quantification of plant diseases at early time points in epidemics, often before visible symptoms appear. These non-destructive, sensor-based methods complement and expand upon traditional visual and molecular approaches to plant disease assessment. They enable the detection of early physiological changes in plants caused by biotic stresses, such as modifications in tissue color, leaf shape, transpiration rate, canopy morphology, and plant density, as well as variations in the interaction of solar radiation with plants. The most relevant areas of application for sensor-based analyses are precision agriculture and plant phenotyping. Precision agriculture focuses on examining spatial heterogeneities within crop stands, while plant phenotyping assesses the appearance and performance of a genotype under distinct environmental conditions, particularly important in disease resistance breeding.

The proven potential of optical techniques in automated, objective, and reproducible detection systems for early disease identification fundamentally transforms agricultural practices. This directly contrasts with the subjectivity, labor-intensiveness, and delayed detection inherent in traditional visual methods. The capacity to detect subtle physiological changes even before visible symptoms appear represents a significant advancement. This progression enables proactive disease management, minimizing pathogen spread and reducing crop losses, effectively moving agriculture from reactive measures to preventive strategies. It also significantly accelerates plant breeding processes by providing high-throughput phenotyping capabilities, leading to the faster development of disease-resistant crop varieties.

Hyperspectral Imaging: Principles, Data Analysis, and Applications

Hyperspectral imaging (HSI) is a fast and nondestructive sensing technology that has achieved remarkable results in plant disease identification. It operates by capturing reflected light from plants across dozens or even hundreds of continuous and narrow spectral bands (nanometer level resolution) within the electromagnetic spectrum, typically from 400 nm to 2500 nm. The data collected forms a three-dimensional "hypercube," where two dimensions represent spatial position (X-Y) and the third dimension (λ) represents the spectral/wavelength information. This allows for the extraction of a complete hyperspectral resolution spectral curve at each pixel, providing a "spectral fingerprint" of the plant's chemical composition.

The principle relies on understanding how plant leaves interact with light through transmission, absorption, and reflection. Different substances within the leaves (e.g., pigments, water, sugars) exhibit unique spectral characteristics, with varying reflectance and absorption values in specific wavebands. For instance, healthy green plants show a small reflection peak near 550 nm, a sharp increase in reflectance near 700 nm (the "red edge phenomenon"), and strong reflectance between 700 and 1200 nm. Plant pathogenesis induces continuous physiological and biochemical reactions that alter these optical properties, making it possible to detect and distinguish diseases at various stages. Data analysis methods for HSI include preprocessing (e.g., image mosaic, segmentation), the use of Vegetation Indices (VIS) like NDVI and GNDVI to represent disease-related changes, and sophisticated machine learning (e.g., K-means clustering, SVM, KNN, Decision Tree) and deep learning algorithms (e.g., Stacked Auto-Encoder (SAE), Deep Belief Network (DBN), Convolutional Neural Networks (CNNs)) for classification. HSI has achieved significant success in plant disease characterization, detection, modeling, and classification. Its applications span precision crop production, horticulture, plant breeding, fungicide screening, and both basic and applied plant research. Despite its power, HSI faces challenges such as the high cost of hyperspectral cameras, environmental sensitivity during spectral acquisition, and time-consuming acquisition and processing, which limit real-time monitoring and widespread agricultural application.

Multispectral Imaging: Principles, Spectral Bands, and Advantages

Multispectral imaging (MSI) is a technique used for plant disease detection that involves capturing data in a limited number of broader spectral bands, as opposed to HSI which uses many narrow and closely spaced bands. The core principle behind MSI for plant disease detection lies in the fact that healthy and diseased plants reflect and absorb light differently across various wavelengths of the electromagnetic (EM) spectrum. Near-infrared (NIR) images, in particular, are crucial because they contain insights not available in the visible spectrum, enabling the identification of abnormal conditions beyond what the human eye can perceive. This allows for early intervention strategies in agriculture, supporting proactive disease management and improving crop yields.

Studies have utilized customized digital single-filter reflex (DSLR) cameras capable of capturing various segments of the EM spectrum depending on the filter used. Specific filters employed include K590 (590–1000 nm), K665 (665–1000 nm), K720 (720–1000 nm), K850 (850–1000 nm), BlueIR (blue 450–500 nm and IR 800–1000 nm), and Hot Mirror (visible 400–800 nm, RGB images). The application of MSI, combined with deep learning algorithms like Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs), aims to enhance the accuracy of plant disease identification. Filters capable of capturing both visible and NIR spectra (K590, K665, and K720) generally perform better in disease identification compared to filters limited to visible or NIR spectra alone. This approach, while providing less detailed spectral information than HSI, is often more practical and cost-effective due to lower data acquisition and processing requirements.

Thermal Imaging (Infrared Thermography): Principles and Physiological Basis of Detection

Infrared thermography, a thermal imaging technology, is used to detect plants stressed by biotic and abiotic factors. The principle relies on the fact that all objects above absolute zero (specifically, above -273 °C) generate infrared radiation. Thermal sensors convert the infrared radiation emitted by a target material into an electrical signal, which is then presented as a colored or monochromatic thermal photograph where color shifts represent thermal fluctuations. The quantity of emitted radiation by a body is determined by its temperature (T) and emissivity (ε).

Physiologically, temperature fluctuations have been linked to pathogen attacks in various instances. During pathogen infection, the physiology of infected plant tissue is modified, including changes in transpiration rate, photosynthetic alteration, salicylic acid accumulation, stomatal conductance, and plant cell death. These modifications lead to changes in leaf temperature, making thermography a valuable tool. For example, infected tomato leaves have shown a reduction in temperature (approximately 0.5–1.3 °C lower) compared to non-infected leaves. Infrared thermography facilitates early and quick disease measurement, often before visible symptoms develop. It is a non-destructive, non-invasive, and non-contact approach. Specific applications include detecting *Venturia inaequalis* (apple scab) on apple plants, identifying fungal infections like gray mold and powdery mildew on rose plants, assessing viral co-infection in sweet potatoes, and discriminating between infected and uninfected wheat plants (e.g., for yellow rust) days before visual signs. Thermography has also been used to diagnose peanut leaf spots, distinguish healthy from basal stem rot infected oil palm trees, and predict pre-symptomatic pathogen influence in cucumbers.

Chlorophyll Fluorescence Imaging: Mechanisms and Utility in Stress Detection

Imaging of chlorophyll *a* fluorescence (CFI) represents an easy, precise, fast, and non-invasive technique that can successfully discriminate plant responses to phytotoxic stress with reproducible results without damaging the plants. The spatio-temporal analyses of fluorescence images provide information about damage evolution, secondary effects, and plant defense responses. The basic principle of CF analysis involves the absorption of a photon by a chlorophyll *a* molecule, which promotes an electron to an excited state. A fluorescence photon is then immediately emitted as the molecule returns to its ground state. CF is one of three mechanisms for energy dissipation in plants, alongside photochemistry and non-photochemical quenching. Five different CF emission signals ($F0$, $F'0$, Fm, $F'm$, and Fs) allow the calculation of other CF parameters, such as maximal PSII quantum yield and effective PSII quantum yield. CFI is particularly useful for detecting early stress responses, often before visible symptoms appear over the leaf lamina or a decline in photosynthesis can be determined by gas exchange measurements. It has become a versatile tool for diagnosing, screening, and phenotyping plants due to its ability to spatially examine heterogeneity within a sample and evaluate changes simultaneously across multiple samples.

Applications include identifying and evaluating crop stress thresholds, integrating with other sensor data (e.g., temperature, humidity) for targeted interventions, and studying the phytotoxic effects of natural compounds. CFI also helps in understanding the dynamics of effects and overall plant responses to treatments, even when visible symptoms are not yet apparent, and can be decisive in studying how plants recover from stress. It avoids misunderstandings caused by "patchy photosynthesis" by capturing fluorescence across the entire leaf at once, providing a more accurate representation of stress-related effects. Currently, CFI is too slow and expensive for widespread commercial diagnostic use in open fields or greenhouses, though mobile and drone-compatible tools are under development.

LiDAR and 3D Scanning for Plant Phenotyping and Disease Assessment

LiDAR (Light Detection and Ranging)-equipped drones have emerged as a transformative tool in precision agriculture. They provide advanced analysis of crop health from an aerial perspective, enabling the early diagnosis of plant diseases that are often undetectable at ground level. Leveraging remote sensing capabilities, LiDAR drones excel in plant pathology detection. They can detect deviations in plant health that are invisible to the naked eye and capture high-resolution data crucial for accurate assessment of crop conditions. These drones are equipped with various sensors, including RGB, multispectral, and thermal sensors, to enhance data acquisition.

In terms of applications, LiDAR drones facilitate timely treatment and effective management of crop diseases. They can monitor extensive agricultural areas with remarkable accuracy and efficiency, overcoming the limitations of traditional crop scouting. By facilitating early detection, LiDAR drones allow farmers to act promptly, minimizing the spread of diseases and enabling targeted interventions. They are also used for continuous monitoring in fruit orchards and for mapping canopy structure, contributing to effective orchard management. Furthermore, through sophisticated data analytics, LiDAR drones can predict areas prone to infections, enabling proactive disease management. The addition of 3D scanning, a recent optical analysis technique, supplies additional information on crop plant vitality. In plant phenotyping, LiDAR assesses the appearance and performance of a genotype under distinct environmental conditions, which is particularly important for disease resistance breeding, evaluating host-pathogen interactions, and assessing the susceptibility of breeding material. This addresses the labor-intensive and costly nature of traditional phenotyping.

Integration of Sensor Technologies with IoT and Drone Platforms

The integration of sensor technologies with Internet of Things (IoT) and drone platforms represents a significant advancement in plant disease detection. Unmanned Aerial Vehicles (UAVs), or drones, have become valuable tools for obtaining detailed data with high spatial, temporal, and spectral resolution. The advantages of drone technology include high spatial resolution, efficiency, usage flexibility, quick detection of plant diseases across large areas with low cost, reliability, and the provision of high-resolution data. The automated procedure involves gathering images of diseased plants using various sensors and cameras, followed by feature extraction, image processing, and the application of machine learning or deep learning algorithms.

Drones revolutionize traditional disease monitoring and treatment by helping to quantify the extent of disease outbreaks and detect/identify symptoms when human assessment is unsuitable or unavailable. UAVs allow farmers to make timely decisions regarding disease management strategies because they can be deployed regularly and provide frequent updates on the spatial distribution of diseases. Additionally, UAVs can reach places that are hard to access with conventional tools, like large fields, dense vegetation, or hilly terrain, allowing for thorough disease monitoring throughout the agricultural landscape. Drones can be equipped with digital (RGB), multispectral, hyperspectral, fluorescent, and thermal infrared-based imaging sensors, coupled with effective algorithms, to efficiently detect, differentiate, and quantify the severity of symptoms induced by various pathogens under field conditions. The integration of sensor technologies with IoT and drone platforms marks a significant leap in overcoming the inherent limitations of traditional methods. While traditional crop monitoring through visual examination is time-consuming, inefficient, and prone to errors, risking future losses , drone-based remote sensing offers a highly successful alternative for quickly detecting diseases in their early stages. This shift from manual, subjective methods to automated, objective, and scalable solutions is crucial for improving food security and meeting global targets. The ability of drones to cover vast areas quickly, provide high-resolution data, and reach inaccessible terrains directly addresses the scalability and accuracy challenges of human observation. Furthermore, the real-time data collection and seamless transfer to central systems facilitated by IoT integration empower farmers with actionable insights for proactive disease management, moving beyond reactive, often late, interventions. This technological convergence represents a critical advancement towards more lucrative and sustainable farming operations.

Table 2: Overview of Advanced Sensor-Based Technologies for Plant Disease Detection

Technology	Principle/Mechanism	Key Applications in Disease Detection	Advantages	Limitations	Relevant Sources
Hyperspectral Imaging (HSI)	Captures light across hundreds of narrow, continuous spectral bands (hypercube); analyzes spectral fingerprints of plant chemistry	Early detection, characterization, modeling, and classification of diseases; precision agriculture, plant breeding, fungicide screening	Non-destructive, objective, high spectral resolution, detects subtle physiological changes before visible symptoms	High cost, environmental sensitivity, time-consuming acquisition/processing, model transferability, data redundancy	
Multispectral Imaging (MSI)	Captures data in a few broader spectral bands (e.g., visible, NIR); analyzes differential light reflection/absorption	Early disease identification, particularly when combining visible and NIR spectra; supports proactive management	More practical and cost-effective than HSI, lower data acquisition/processing, identifies abnormal conditions beyond human eye	Less spectral detail than HSI, may not detect very subtle changes	

Technology	Principle/Mechanism	Key Applications in Disease Detection	Advantages	Limitations	Relevant Sources
Thermal Imaging (Infrared Thermography)	Measures plant surface temperature based on emitted infrared radiation; detects temperature fluctuations	Early detection of pathogen attacks, monitoring physiological changes (transpiration, photosynthesis), distinguishing infected tissue	Non-destructive, non-invasive, non-contact, sensitive to early physiological changes, rapid measurement	Affected by environmental factors, resolution can impact cost/accuracy	
Chlorophyll Fluorescence Imaging (CFI)	Measures chlorophyll *a* fluorescence emission; quantifies energy dissipation in photosynthetic apparatus	Early stress detection (biotic/abiotic), diagnosing, screening, phenotyping, studying recovery processes	Non-invasive, fast, cost-effective (for research), detects stress before visible symptoms or photosynthesis decline	Too slow and expensive for widespread commercial field use, sensitive to controlled conditions	
LiDAR and 3D Scanning	Uses pulsed laser light to measure distance and create 3D models; analyzes canopy structure and plant vitality	Early diagnosis of diseases, plant phenotyping (genotype performance), disease resistance breeding, mapping canopy structure	High-resolution data, detects ground-level undetectable diseases, covers vast areas, objective 3D information	Equipment cost, data processing complexity	
Drones (UAVs) with Integrated Sensors & IoT	Platforms for carrying various sensors (RGB, multi/hyperspectral, thermal, fluorescence); data transfer via IoT	Rapid, large-area monitoring; early warning systems; targeted interventions;	High spatial/temporal/spectral resolution, efficiency, flexibility, low cost (per area), real-time data for informed decisions	Regulatory constraints, battery life, data processing infrastructure needs	

Technology	Principle/Mechanism	Key Applications in Disease Detection	Advantages	Limitations	Relevant Sources
		reaching inaccessible areas; quantifying outbreaks			

2. **Artificial Intelligence and Deep Learning for Automated Disease Diagnosis**

The advent of Artificial Intelligence (AI) and Deep Learning (DL) has revolutionized the field of plant disease detection, offering automated, highly accurate, and efficient diagnostic capabilities that far surpass traditional methods. These technologies primarily leverage image-based analysis, transforming the way plant health is monitored and managed.

Fundamentals of Image Processing: Preprocessing, Segmentation, and Feature Extraction

The foundation of AI-driven plant disease detection systems lies in robust image processing pipelines. This typically begins with **image acquisition**, where relevant images of plant organs (primarily leaves, but also stems and fruits) are captured using high-resolution digital cameras, smartphones, or drone-mounted sensors. The quality of these images is crucial for subsequent analysis.

Following acquisition, **image preprocessing** is applied to enhance the image data by suppressing undesired distortions, removing noise, or enhancing features important for further processing. Common preprocessing techniques include filtering (e.g., Gabor filter), noise removal, image enhancement (e.g., histogram equalization, color conversion), resizing to a consistent input dimension, and normalization. This step ensures that the model focuses on pertinent characteristics for precise disease classification.

Next, **image segmentation** is performed to simplify the image representation and distinguish the object of interest (e.g., diseased plant parts) from the background. This process is fundamental for feature extraction and pattern recognition. Various techniques are employed, such as K-means clustering, the Chan-Vase method, or using color scales like CIELAB to separate diseased and unaffected portions. Advanced deep learning models like U-Net are also highly effective for pixel-level segmentation of diseased regions.

Finally, **feature extraction** aims to identify and quantify relevant characteristics from the processed images that can be used to determine the meaning of a given sample. These features typically include color, texture, shape, and patterns. Traditional methods involve hand-crafted features like color co-occurrence, Local Binary Patterns (LBP), Gray-Level Co-occurrence Matrix (GLCM), and Histogram of Oriented Gradients (HOG). However, a significant advantage of deep learning models is their ability to automatically extract complex features directly from raw image data, eliminating the need for manual feature engineering.

Convolutional Neural Networks (CNNs) for Image Classification

Convolutional Neural Networks (CNNs) have emerged as a dominant force in image recognition and classification, proving exceptionally effective for automated plant disease diagnosis. CNNs operate by automatically extracting relevant features from input images and mapping them to corresponding disease classes. A typical CNN architecture comprises several key layers: **convolutional layers** which apply learnable filters to detect various patterns like edges, textures, and more complex features; **pooling layers** that reduce the spatial dimensions of feature maps, thereby improving efficiency and helping to prevent overfitting; and **fully connected layers** that interpret the extracted features and make final predictions. Non-linear activation functions, such as Rectified Linear Unit (ReLU), are applied after convolutional layers to enable the network to learn intricate patterns.

Detailed Architectures: AlexNet, VGG, ResNet, Inception, DenseNet, MobileNet

Several prominent CNN architectures have been successfully adapted for plant disease detection:

- **AlexNet:** An influential early CNN, AlexNet consists of eight layers: five convolutional layers and three fully connected (or Artificial Neural Network – ANN) layers. It utilizes ReLU activation, overlapping max pooling, and Local Response Normalization (LRN). Dropout layers are incorporated to prevent overfitting, particularly in its high-neuron count fully connected layers. AlexNet has demonstrated high accuracy, achieving 99.35% on a held-out test set from the PlantVillage dataset.
- **VGG:** The VGG family of networks, such as VGG16 (13 convolutional, 3 fully connected layers) and VGG19 (16 convolutional, 3 fully connected layers), are characterized by their depth and the consistent use of small 3x3 kernel filters throughout their convolutional layers. This uniform architecture makes them relatively easy to understand and implement. VGG models have shown strong performance in plant disease classification, with VGG-16 achieving around 95.2% accuracy and VGG19 exceeding 95% accuracy in various studies.
- **ResNet:** Residual Networks (ResNet), including variants like ResNet50, ResNet101, ResNet152V2, ResNet34, and ResNet197, introduced the groundbreaking concept of residual blocks or “skip connections”. These connections allow the model to bypass one or more layers, directly passing information and gradients, which effectively mitigates the vanishing gradient problem and enables the training of extremely deep networks. ResNet50 has achieved accuracies such as 96.35% for tomato leaf disease classification, and ResNet197 has reached 99.58% accuracy in broader plant disease classification tasks.
- **Inception:** The Inception architecture, first introduced as GoogLeNet (InceptionV1) and evolving into versions like InceptionV3 and Inception-ResNet, features “Inception modules”. These modules employ multiple parallel branches with different filter sizes (e.g., 1x1, 3x3, 5x5 convolutions) and 1x1 convolutions for dimensionality reduction, allowing the network to capture a wide range of features efficiently. GoogLeNet achieved a high accuracy of 99.56% for tomato plant disease identification, and InceptionV3, when optimized with Particle Swarm Optimization (PSO), reached 98.7% accuracy.
- **DenseNet:** Dense Convolutional Networks (DenseNet), including DenseNet121, DenseNet169, and DenseNet201, feature a unique “dense connectivity” pattern where each layer is directly connected to every other subsequent layer in a feed-forward manner. This dense connectivity alleviates the vanishing gradient problem, encourages feature reuse, and substantially improves parameter efficiency. DenseNet201 has demonstrated strong performance, achieving a validation accuracy of 98.70% in plant disease diagnosis.
- **MobileNet:** MobileNet architectures, such as MobileNetV2, are lightweight CNNs specifically optimized for mobile and edge devices. They achieve high accuracy with low latency and computational cost by utilizing “inverted residual blocks” and “linear bottlenecks,” along with depthwise separable convolutions. MobileNet’s efficiency makes it a practical choice for real-world agricultural applications, allowing for fast and accurate disease detection on devices with limited resources.

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) for Sequential Data Analysis

Recurrent Neural Networks (RNNs) are a class of deep learning models specifically designed to handle sequential data, where the order of elements carries significance. Unlike traditional feedforward networks, RNNs possess connections that loop back to previous time steps, allowing them to retain a "memory" of past inputs and learn temporal dependencies within the data. This makes them suitable for tasks where the length of infected regions varies, as they can process sequences of variable length.

A significant advancement within RNNs is the **Long Short-Term Memory (LSTM)** network. LSTMs are an improved variant of RNNs engineered to mitigate the vanishing gradient problem, a common issue in traditional RNNs that hinders learning over long sequences. LSTMs achieve this by incorporating a unique "gated cell" structure, comprising input, output, and forget gates. These gates regulate the flow of information into and out of the cell, allowing LSTMs to remember values over arbitrary time intervals and preserve error signals during backpropagation. LSTMs are used for feature extraction and classification in plant disease identification, and have been applied for time series prediction of pests and diseases, often integrating meteorological factors.

Object Detection Models: YOLO for Real-time Disease Localization

Object detection models are crucial for not only classifying diseases but also precisely localizing them within an image by drawing bounding boxes around affected areas. The **YOLO (You Only Look Once)** algorithm is a prominent real-time object detection system that processes images through a single forward pass of a neural network, performing both object recognition and bounding box regression simultaneously. This single-pass efficiency allows YOLO to process images at high speeds, making it ideal for real-time applications.

YOLO operates by dividing an input image into a grid of cells, with each cell responsible for localizing and predicting the class of an object whose center falls within it. To enhance accuracy, YOLO utilizes anchor boxes of varying sizes and aspect ratios, along with techniques like Intersection Over Union (IoU) to evaluate bounding box accuracy and Non-Max Suppression (NMS) to eliminate redundant detections. Recent iterations, such as the improved YOLOv8 model (e.g., SerpensGate-YOLOv8), incorporate advanced components like a **Backbone** for feature extraction (e.g., using C2f-DySnakeConv, SPPELAN, Super Token Attention (STA)), a **Neck** for multi-scale feature fusion, and a **Head** for final classification and detection. These models produce multi-scale output feature maps (e.g., 20x20, 40x40, 80x80) to effectively detect plant disease regions of varying sizes and complex morphological characteristics. Improved YOLOv8 models have shown significant performance gains, with one achieving a 3.3% improvement in mean Average Precision (mAP@0.5) over the original YOLOv8.

Semantic Segmentation Models: U-Net for Pixel-Level Disease Mapping

Semantic segmentation is a more granular approach than object detection, aiming to classify each pixel in an image into a specific category, thereby precisely mapping diseased regions at a pixel level. The **U-Net** architecture is particularly effective for such precise segmentation tasks in plant disease detection, enabling the distinction between healthy and infected areas.

U-Net is characterized by its symmetric "U"-shaped encoder-decoder architecture with crucial "skip connections". The **encoder** (contracting path) captures high-level contextual features by applying convolutional layers followed by max-pooling to reduce spatial dimensions while increasing feature channels. The **decoder** (expanding path) then mirrors this process, using up-sampling to restore the original resolution. The skip connections are vital, as they concatenate feature maps from the encoder to corresponding layers in the decoder, ensuring that fine-grained spatial details lost during down-sampling are preserved and integrated into the up-sampled feature maps. U-Net models often employ regularization techniques like dropout, batch normalization, and ReLU activation to prevent overfitting and improve learning. When trained on high-quality "Leaf Disease Segmentation" datasets with annotated regions of unhealthy leaf tissue, U-Net models have achieved high validation accuracies, with one study reporting 98.99%.

The Role of Transfer Learning in Model Development

Transfer learning is a common and highly effective approach in deep learning for tasks where abelled data might be limited. Instead of training a model from scratch, transfer learning involves fine-tuning a pre-trained model (e.g., VGG, ResNet, Inception, MobileNet) that has already learned rich features from a very large, general-purpose image dataset like ImageNet. This process significantly reduces the computational load and training time required, while simultaneously improving feature extraction capabilities, enhancing overall accuracy, and boosting the robustness of the model, especially when applied to specific plant disease datasets.

Enhancing Transparency with Explainable AI (XAI): Grad-CAM, LIME, SHAP

As deep learning models become more complex and achieve higher accuracies, they often operate as "black boxes," making it difficult to understand *why* a particular prediction was made. This lack of transparency can hinder user trust and validation, which is a significant concern in critical applications like plant disease diagnosis. Explainable AI (XAI) addresses this challenge by providing interpretable insights into the model's decision-making process, thereby enhancing transparency and usability. XAI techniques are crucial for validating and trusting the system's predictions in real-world agricultural scenarios.

Key XAI techniques include:

- **Grad-CAM (Gradient-weighted Class Activation Mapping):** A model-specific method for CNNs that provides visual explanations by highlighting the influential regions in the input image that contributed most to the model's prediction. For instance, when diagnosing apple scab, Grad-CAM can reveal if the model is correctly focusing on the characteristic spots and lesions associated with the disease.
- **LIME (Local Interpretable Model-agnostic Explanations) and SHAP (Shapley Additive Explanations):** These are more general XAI techniques that can pinpoint which features or regions contributed most to a prediction, enhancing transparency and aiding quality control.

Emerging Paradigms: Federated Learning for Decentralized Training

Federated learning represents an emerging paradigm that addresses concerns related to data privacy and computational decentralization in AI model training. This approach enables decentralized model training on edge devices, such as smartphones or farm-based sensors, without requiring the raw image data to be uploaded to a central server. Farmers can collaboratively train a shared global model by contributing their local model updates, thereby preserving data privacy while still benefiting from a collectively improved AI system. This approach is particularly promising for agricultural settings where data privacy is paramount and internet connectivity might be inconsistent, allowing for more robust and widely applicable plant disease detection solutions.

Table 3: Summary of Key Deep Learning Architectures for Plant Disease Detection

Architecture	Key Characteristics	Typical Application in Plant Disease Detection	Reported Performance (Example)	Relevant Sources
AlexNet	8 layers (5 Conv, 3 FC), ReLU, overlapping max pooling, LRN, dropout	Image classification, early disease diagnosis	99.35% accuracy (PlantVillage)	
VGG (VGG16, VGG19)	Deep (16/19 layers), uniform 3x3 kernel filters, multiple pooling layers	Image classification, feature extraction, disease identification	VGG16: 95.2% accuracy ; VGG19: >95% accuracy	
ResNet (ResNet50, etc.)	Residual blocks (skip connections) to overcome vanishing gradients, enables very deep networks	Image classification, phenotyping of sick tissue, disease diagnosis	ResNet50: 96.35% accuracy ; ResNet197: 99.58% accuracy	
Inception (GoogLeNet, InceptionV3)	Inception modules with parallel multi-scale convolutions, 1x1 conv for dimensionality reduction	Image classification, enhancing accuracy in disease classification	GoogLeNet: 99.56% accuracy ; InceptionV3: 98.7% accuracy with PSO	
DenseNet (DenseNet121, etc.)	Dense connectivity (each layer connected to all subsequent layers), feature reuse, parameter efficiency	Plant disease diagnosis, image classification	DenseNet201: 98.70% validation accuracy	
MobileNet (MobileNetV2)	Lightweight, optimized for mobile/edge devices, inverted residual blocks, linear bottlenecks	Efficient disease detection on mobile devices, real-time classification	High accuracy with low latency	
YOLO (You Only Look Once)	Single-pass object detection, real-time bounding box prediction and classification	Real-time disease localization, identifying disease foci	Improved YOLOv8: 3.3% mAP@0.5 improvement	
U-Net	Symmetric encoder-decoder with skip connections, pixel-level classification	Semantic segmentation of diseased areas, precise mapping of disease regions	98.99% validation accuracy	
RNN/LSTM	Recurrent connections for sequential data, LSTMs handle long-term dependencies via gated cells	Analysis of temporal disease progression, time series prediction of pests/diseases	Effective in time series prediction	

3. Key Datasets for Training and Validation

The development and validation of robust AI and deep learning models for plant disease detection heavily rely on the availability of high-quality, diverse, and well-annotated datasets. Several publicly available datasets have become instrumental in advancing research in this field.

Overview of Publicly Available Datasets: PlantVillage, PlantCLEF, PlantDoc

- **PlantVillage:** This is one of the most widely used datasets for plant disease detection research. It comprises 61,486 images of plant leaves and backgrounds, categorized into 39 different plant diseases across 38 distinct classes (crop-disease pairs), including healthy leaves. To enhance diversity and simulate various background conditions, the dataset was created with six different augmentation techniques: scaling, rotation, noise injection, gamma correction, image flipping, and PCA color augmentation. It is available in both augmented and non-augmented subsets.
- **PlantCLEF:** This dataset is primarily associated with challenges focused on image-based plant species identification in high-resolution vegetation plot images, known as quadrats (typically 0.5 to 1 square meter in size). The challenge involves a multi-label classification task, aiming to predict all plant species present within a quadrat image from a vast number of potential species (thousands). While the test data consists of multi-label plot images, the training data is often composed of single-label images of individual plants or plant parts. For instance, PlantCLEF 2022 included 4 million images covering 80,000 species, and PlantCLEF 2024 introduced a new test set with thousands of multi-label images covering over 800 species. PlantCLEF addresses the complexities of fine-grained classification and the impact of environmental variability in real-world settings.
- **PlantDoc:** The PlantDoc dataset consists of high-quality images from 27 plant disease classes and has been utilized for developing generalizable models capable of performing accurately in diverse conditions. To improve generalization to real-world settings, PlantDoc is often combined with web-sourced images. A notable limitation of this dataset, however, is that most of its images were collected in controlled environments, which can hinder a model's ability to generalize to the varied and intricate ways plant diseases manifest in the field.

Other publicly available datasets mentioned in the literature include "New Plant Diseases" (approximately 87,000 RGB images across 38 classes) , IPM Images, APS Images, and PLD. Additionally, specialized datasets like a manually collected image dataset of sugarcane leaf disease, containing 2,569 images across five categories (Healthy, Mosaic, Redrot, Rust, Yellow disease), have been developed with smartphone-captured images to maintain diversity.

Dataset Characteristics, Image Types, and Data Augmentation Strategies

The characteristics of datasets used for plant disease detection vary significantly, impacting model performance and generalizability. **Image types** predominantly include RGB images, which are the most common input for visual recognition tasks. However, advanced sensor technologies contribute multispectral and hyperspectral images, often collected in controlled environments, providing richer spectral information beyond the visible spectrum. Near-Infrared (NIR) images, in particular, are considered favorable for identifying plant diseases as they provide unseen information that supplements human visual perception.

Data augmentation strategies are crucial for addressing data scarcity, increasing dataset diversity, and improving model generalization and robustness, especially when dealing with limited datasets. These techniques artificially expand the training dataset by creating modified versions of existing images. Common augmentation methods include scaling, rotation, noise injection (e.g., Gaussian noise to enhance resilience to sensor noise), gamma correction, image flipping (horizontal/vertical to simulate natural variations in leaf orientation), and PCA color augmentation. Affine transformations are also employed to compensate for perspective distortions from different camera angles, and luminance adjustments simulate various lighting conditions encountered in real-world scenarios. The use of dropout techniques during model training also helps prevent overfitting and improves generalization.

Despite these efforts, significant challenges persist in data collection and curation. Most current detection methods rely heavily on lab-captured images, which may not generalize well to the diverse and uncontrolled conditions of real-world agricultural settings. Collecting and annotating large-scale datasets that encompass all plant species and disease variations is an enormous and labor-intensive task. Consequently, data scarcity and the limited availability of diverse, abelled training data remain significant challenges for developing truly robust and generalizable models.

Table 4: Prominent Publicly Available Datasets for Plant Disease Detection

Dataset Name	Primary Focus	Number of Images	Number of Classes/Diseases	Key Features & Image Types	Relevant Sources
PlantVillage	Plant disease classification	61,486	39 diseases / 38 classes (crop-disease pairs)	RGB images of leaves and backgrounds; created with 6 augmentation techniques (scaling, rotation, noise, gamma correction, flipping, PCA color) for diversity	
PlantCLEF	Plant species identification in vegetation plots	4M (training), thousands (test)	80k species (2022), 800+ species (2024)	High-resolution RGB quadrat images (0.5-1 sq meter); multi-label classification challenge; training often single-label, test multi-label	
PlantDoc	Generalizable plant disease detection in diverse conditions	2,598 (PlantDoc)	27 disease classes	High-quality images; often combined with web-sourced images; potential limitation: mostly controlled environment images	
New Plant Diseases	Plant disease classification	~87,000	38 classes	RGB images of healthy and diseased crop leaves; divided into training/validation/test sets	
Sugarcane Leaf Disease	Sugarcane leaf disease detection	2,569	5 categories (Healthy, Mosaic, Redrot, Rust, Yellow)	Images captured with smartphones for diversity	

6. Persistent Challenges and Future Directions

Despite the remarkable advancements in plant disease detection driven by sensor technologies and artificial intelligence, several persistent challenges must be addressed to realize the full potential of these innovations for sustainable agriculture.

Addressing Data Scarcity and Enhancing Dataset Diversity for Generalization

A significant challenge in developing robust deep learning models for plant disease detection is the inherent **data scarcity**. Deep learning models require vast amounts of labeled training data to learn complex patterns effectively. This limitation is particularly pronounced for rare or emerging diseases, where labeled samples are scarce. Furthermore, models trained predominantly on lab-captured images often struggle to **generalize** well to diverse, uncontrolled real-world environments, which feature varying backgrounds, lighting conditions, and occlusions. This discrepancy between training data and real-world application hinders practical deployment.

To overcome these limitations, **data augmentation techniques** are crucial. These methods artificially expand the diversity of existing datasets by applying transformations such as scaling, rotation, noise injection (e.g., Gaussian noise), gamma correction, image flipping, and PCA color augmentation. Affine transformations can compensate for perspective distortions, and luminance adjustments simulate various lighting conditions, making models more robust to real-world variability. **Transfer learning** with pre-trained models also provides a powerful solution, allowing models to leverage features learned from large, general datasets and adapt them to specific plant disease tasks with limited data. Combining diverse datasets, such as PlantDoc with web-sourced images, has also proven effective in improving generalization capabilities. Continued efforts are needed to create and make more publicly available datasets that represent a broader range of plant species, disease stages, and environmental conditions.

Mitigating Environmental Variability and Improving Model Robustness

Real-world agricultural settings present complex and dynamic environmental factors that significantly impact the accuracy and reliability of automated disease detection systems. These include occlusions from leaves, highly variable lighting conditions (e.g., shadows, direct sunlight), background clutter, dust, water on leaves, and uneven terrain. Such conditions can obscure subtle or early signs of disease, making detection challenging for both human observers and automated systems.

To mitigate these challenges and improve **model robustness**, enhanced data augmentation techniques, such as adding Gaussian noise, are employed to build resilience against sensor noise and lighting variations. It is essential for models to be capable of classifying images accurately across various lighting conditions, orientations, and sizes. The integration of multi-scale feature extraction, as seen in object detection models like YOLO, allows systems to capture symptoms of varying sizes and patterns effectively. Furthermore, advanced architectural modules like Super Token Attention (STA), Dynamic Snake Convolution (DSConv), and Spatial Pyramid Pooling and Efficient Layer Aggregation Network (SPPELAN), used in models like YOLOv8, are specifically designed to improve robustness to complex backgrounds, capture irregular disease boundaries, and enhance feature representation quality.

Computational Demands and the Path to Real-Time, Edge-Device Deployment

A significant barrier to the widespread adoption of AI-driven plant disease detection, particularly for real-time, in-field applications, is the high **computational demand** of deep learning models. Larger models require substantial processing power and memory, which can restrict their practical use on resource-limited devices commonly found in agricultural settings. Even advanced sensor technologies like hyperspectral imaging can involve long acquisition and processing times, limiting their utility for immediate, actionable insights.

The path to **real-time, edge-device deployment** necessitates the development of more computationally efficient solutions. Lightweight architectures, such as MobileNet, are specifically optimized for mobile and edge devices, offering low latency and computational efficiency while maintaining high accuracy. The focus on model compactness and efficiency is a key research direction. Techniques like online knowledge distillation can facilitate cross-species knowledge transfer, potentially reducing individual model sizes. Moreover, improving data processing speed through modern on-chip calculation systems (e.g., FPGAs) and developing specific intellectual property kernels are crucial steps toward achieving real-time identification and control strategies directly in the field.

The "Black Box" Problem: Advancing Model Interpretability and Trust

Deep learning models, despite their impressive performance, often operate as "black boxes," meaning their internal decision-making processes are opaque and difficult for humans to understand. This lack of transparency can erode user trust and hinder the validation of model predictions, which is a critical concern in high-stakes applications like plant disease diagnosis. Farmers and agricultural experts need to understand *why* a model is predicting a certain disease to confidently apply treatments and manage their crops.

Explainable AI (XAI) techniques are emerging as a vital solution to this "black box" problem. XAI aims to provide human-understandable explanations for the decisions made by complex machine learning models, thereby enhancing transparency and usability. In the context of plant disease detection, methods like **Grad-CAM (Gradient-weighted Class Activation Mapping)** are particularly useful. Grad-CAM, a model-specific technique for CNNs, generates visual heatmaps that highlight the influential regions in the input image that most contributed to the model's prediction. This allows users to visually verify if the model is focusing on the characteristic spots or lesions associated with a particular disease. Other XAI techniques like LIME (Local Interpretable Model-agnostic Explanations) and SHAP (Shapley Additive Explanations) also contribute by pinpointing the features or data points that drive a prediction. By making AI decisions more transparent, XAI fosters greater trust and facilitates the practical adoption of these advanced systems in agriculture.

Cost-Effectiveness and Accessibility for Widespread Adoption

The high cost associated with advanced sensor technologies, such as hyperspectral cameras, currently limits their widespread agricultural application, particularly for smallholder farmers or in developing regions. While low-cost thermal cameras exist, they may offer lower resolution, potentially impacting the accuracy of early disease detection.

To promote **cost-effectiveness and accessibility**, research efforts are focusing on developing low-cost, smartphone-assisted diagnosis systems, leveraging the ubiquitous presence of mobile devices. Optimizing deep learning models for resource-constrained devices, as exemplified by lightweight architectures like MobileNet, is crucial for enabling practical field deployment through mobile applications or embedded systems. Furthermore, emerging paradigms like federated learning can reduce infrastructural costs by enabling decentralized model training, thereby avoiding the need for expensive central server infrastructure and large data transfers. These advancements aim to democratize access to advanced plant disease detection capabilities, making them viable for a broader range of agricultural stakeholders.

Interdisciplinary Research and Integrated Pest Management Strategies

Plant diseases are complex phenomena, influenced by intricate interactions between the plant host, pathogens, and various environmental factors. Effective disease management therefore requires a holistic and **interdisciplinary approach**. The current focus on automated detection systems needs to be seamlessly integrated into broader **Integrated Pest Management (IPM) strategies**.

IPM combines biological, cultural, physical, and chemical tools to minimize damage while promoting environmental sustainability. Future research should emphasize developing models that can differentiate between biotic stresses (diseases) and abiotic stresses (e.g., drought, nutrient deficiencies), as their symptoms can sometimes be similar. This requires models that can remove the effects of other biotic or abiotic stresses from disease identification. Integrating observations from advanced detection systems with existing IPM practices and soil health assessments can lead to more targeted and sustainable interventions, reducing reliance on broad-spectrum chemical treatments. The increasing impact of climate change also necessitates the development of integrated and climate-smart pest management strategies that can adapt to evolving disease patterns and environmental conditions. Collaborative research across plant pathology, agricultural engineering, computer science, and environmental science will be essential to develop comprehensive, adaptive, and sustainable solutions for plant disease management.

Table 5: Major Challenges and Proposed Solutions in Automated Plant Disease Detection

Challenge	Description	Proposed Solutions & Techniques	Relevant Sources
Data Scarcity & Lack of Diversity	Deep learning requires vast labeled data; limited for rare diseases; lab-captured images don't generalize to real-world variability.	Data augmentation (scaling, rotation, noise, flipping, affine, luminance); Transfer learning with pre-trained models; Combining diverse datasets; More public datasets.	
Environmental Variability	Complex field conditions (occlusions, lighting, background clutter, dust, water) obscure symptoms and affect accuracy.	Enhanced data augmentation (e.g., Gaussian noise); Models robust to varying conditions (lighting, orientation, size); Multi-scale feature extraction (YOLO); Advanced architectural modules (STA, DSConv, SPPELAN).	
Computational Demands	Large deep learning models are computationally expensive, hindering real-time, edge-device deployment.	Lightweight architectures (MobileNet); Model compactness and efficiency; Online knowledge distillation; On-chip calculation systems (FPGA).	
"Black Box" Problem (Lack of Interpretability)	Deep learning models' opaque decision-making reduces user trust and validation in critical applications.	Explainable AI (XAI) techniques (Grad-CAM, LIME, SHAP) to provide human-understandable explanations and highlight influential regions.	
Cost-Effectiveness & Accessibility	High cost of advanced sensors limits widespread adoption, especially for smallholders.	Development of low-cost, smartphone-assisted diagnosis systems; Optimization for resource-constrained devices; Federated learning for decentralized training.	
Interdisciplinary Integration	Plant diseases are complex; effective management requires holistic, integrated strategies.	Integrated and climate-smart pest management; Combining detection with IPM and soil health assessments; Research differentiating biotic/abiotic stresses; Fostering cross-disciplinary collaboration.	

7. Conclusion

The field of plant disease detection has witnessed a profound transformation, evolving from traditional, often subjective and labor-intensive methods to highly sophisticated, automated, and objective approaches. This review has highlighted the critical importance of early and accurate disease detection for global food security, economic stability, and environmental sustainability, emphasizing the substantial yield losses and economic impacts currently caused by plant pathogens. The inherent limitations of conventional techniques, such as visual inspection's subjectivity and microbiological methods' time-consuming nature, created a compelling imperative for technological advancement.

Modern sensor-based technologies, including hyperspectral, multispectral, thermal, and chlorophyll fluorescence imaging, alongside LiDAR and 3D scanning, have revolutionized the ability to detect subtle physiological changes in plants even before visible symptoms appear. These non-destructive methods provide objective, reproducible data crucial for precision agriculture and high-throughput plant phenotyping. The integration of these sensors with IoT and drone platforms further amplifies their capabilities, enabling large-scale, real-time monitoring and targeted interventions, thereby significantly overcoming the scalability and efficiency constraints of human-centric approaches.

Artificial intelligence and deep learning, particularly Convolutional Neural Networks (CNNs) with their diverse architectures (e.g., AlexNet, VGG, ResNet, Inception, DenseNet, MobileNet), have become central to automated disease diagnosis. These models excel at image classification, object detection (YOLO), and pixel-level segmentation (U-Net), demonstrating impressive accuracies in identifying and localizing plant diseases. The strategic use of transfer learning has accelerated model development, enabling high performance even with limited specialized datasets. Emerging areas like Explainable AI (XAI) are addressing the "black box" problem, fostering trust and interpretability, while federated learning promises privacy-preserving, decentralized training.

Despite these significant strides, persistent challenges remain. Data scarcity, particularly for real-world conditions, and the need to enhance dataset diversity for robust generalization are critical. Mitigating the effects of environmental variability and improving model robustness in complex field settings are ongoing research priorities. The computational demands of advanced deep learning models necessitate further development of lightweight architectures and efficient edge-device deployment solutions for real-time applications. Finally, ensuring the cost-effectiveness and accessibility of these technologies for all farmers, and integrating them seamlessly into comprehensive, interdisciplinary Integrated Pest Management strategies, are crucial for their widespread adoption and ultimate impact.

Future research should prioritize the creation of larger, more diverse, and meticulously annotated datasets that accurately reflect real-world agricultural conditions. Further exploration into lightweight and energy-efficient deep learning architectures, coupled with advancements in on-chip processing, will be vital for scalable, real-time, in-field deployment. Deepening the integration of XAI techniques will enhance model transparency and user confidence, facilitating practical application. Moreover, fostering interdisciplinary collaboration among plant pathologists, agricultural engineers, and AI researchers will be essential to develop holistic, climate-smart disease management solutions that can adapt to evolving environmental challenges. By addressing these priorities, advanced plant disease detection technologies hold immense transformative potential for reducing crop losses, enhancing agricultural yields, improving food safety, and contributing significantly to global food security and sustainable farming practices.

इन स्रोतों से जानकारी ली गई

1. Plant Disease Detection by Imaging Sensors – Parallels and Specific Demands for Precision Agriculture and Plant Phenotyping - APS Journals, https://apsjournals.apsnet.org/doi/10.1094/PDIS-03-15-0340-FE 2. Revolutionizing agriculture with artificial intelligence: plant disease detection

methods, applications, and their limitations - PMC, https://pmc.ncbi.nlm.nih.gov/articles/PMC10965613/
2. Key Challenges in Plant Pathology in the Next Decade | Phytopathology® - APS Journals, https://apsjournals.apsnet.org/doi/10.1094/PHYTO-04-24-0137-KC
3. Emerging Plant Diseases and Global Food Security | Epidemiology - APS Journals, https://apsjournals.apsnet.org/doi/book/10.1094/9780890546383
4. Economic impact | EFSA - European Union, https://www.efsa.europa.eu/en/plh4l/economic-impact
5. Revolutionizing agriculture with artificial intelligence: plant disease detection methods, applications, and their limitations - Frontiers, https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2024.1356260/full
6. Plant Disease Detection Techniques: A Review - Amity University Noida, https://amity.edu/icactm/Proceeding/Paper%20Index%20Content/24%20T1%20P7%20ID%2036.pdf
7. Visual inspection - (Intro to Botany) - Vocab, Definition, Explanations | Fiveable, https://library.fiveable.me/key-terms/introduction-botany/visual-inspection
8. Plant Disease Diagnosis: Techniques and Tools - Number Analytics, https://www.numberanalytics.com/blog/plant-disease-diagnosis-techniques-tools
9. Detecting and Managing Crop Diseases with Lidar Drones, https://www.agrisensedrones.com/managing-crop-diseases-lidar-drones/
10. Plant Disease Detection Using Computer Vision in Agriculture | ImageVision.ai, https://imagevision.ai/blog/plant-disease-detection-using-computer-vision-for-early-diagnosis-and-prevention/
11. Real-Time PCR and Its Application in Plant Disease Diagnostics - CORE, https://core.ac.uk/download/pdf/234687067.pdf
12. Serological Tests - Springer Nature Experiments, https://experiments.springernature.com/articles/10.1007/978-1-0716-0334-5_30
13. Applications of Drone for Crop Disease Detection and Monitoring: A Review - ResearchGate, https://www.researchgate.net/publication/387944874_Applications_of_Drone_for_Crop_Disease_Detection_and_Monitoring_A_Review
14. (PDF) Plant Disease Detection using ResNet - ResearchGate, https://www.researchgate.net/publication/371240835_Plant_Disease_Detection_using_ResNet
15. Plant Leaf Disease Detection Using Deep Learning: A Multi-Dataset Approach - MDPI, https://www.mdpi.com/2571-8800/8/1/4
16. Hyperspectral Sensing of Plant Diseases: Principle and Methods, https://www.mdpi.com/2073-4395/12/6/1451
17. (PDF) Hyperspectral Imaging: A Tool for Plant Disease Detection - ResearchGate, https://www.researchgate.net/publication/378108469_Hyperspectral_Imaging_A_Tool_for_Plant_Disease_Detection
18. Multispectral Plant Disease Detection with Vision Transformer ..., https://pmc.ncbi.nlm.nih.gov/articles/PMC10611079/
19. Plant Disease Detection Using Multispectral Imaging - ResearchGate, https://www.researchgate.net/publication/372349128_Plant_Disease_Detection_Using_Multispectral_Imaging
20. (PDF) Concept and Application of Infrared Thermography for Plant ...,

https://www.researchgate.net/publication/364741970_Concept_and_Application_of_Infrared_Thermography_for_Plant_Disease_Measurement
21. Early detection of plant disease using infrared thermal imaging - ResearchGate, https://www.researchgate.net/publication/260278042_Early_detection_of_plant_disease_using_infrared_thermal_imaging
22. Imaging of Chlorophyll a Fluorescence in Natural ... - Frontiers, https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2020.583590/full
23. Applications of Drone for Crop Disease Detection and Monitoring: A Review - AWS, https://sdiopr.s3.ap-south-1.amazonaws.com/2025/JANUARY/16_Jan_2025/2024_ARJA_128118/Ms_ARJA_128118.pdf
24. (PDF) A review on automated plant disease detection: motivation, limitations, challenges, and recent advancements for future research - ResearchGate, https://www.researchgate.net/publication/391610335_A_review_on_automated_plant_disease_detection_motivation_limitations_challenges_and_recent_advancements_for_future_research
25. Applying image processing technique to detect plant diseases - CiteSeerX, https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=f0873dc46d0dcacde2e9a50b7ec99388bf7dcf88
26. A Review of Image Processing Techniques Common in Human and Plant Disease Diagnosis - MDPI, https://www.mdpi.com/2073-8994/10/7/270
27. [PDF] Plant Disease Detection Using Image Processing - Semantic Scholar, https://www.semanticscholar.org/paper/Plant-Disease-Detection-Using-Image-Processing-Khirade-Patil/575467ca9dc8d7f687fe2f490f6b18932b5c45bd
28. Plant Disease Classification using AlexNet - Analytics Vidhya, https://www.analyticsvidhya.com/blog/2023/02/plant-disease-classification-using-alexnet/
29. Enhancing plant disease detection through deep learning: a Depthwise CNN with squeeze and excitation integration and residual skip connections - Frontiers, https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2024.1505857/full
30. Using Deep Learning for Image-Based Plant Disease Detection - Frontiers, https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2016.01419/full
31. Deep Learning VGG19 Model for Precise Plant Disease Detection - AWS, https://arccarticles.s3.amazonaws.com/OnlinePublish/Final-article-attachemnt-with-doi-D-6220-6089603e9087340b9bdcbbb1.pdf
32. Plant Diseased Lesion Image Segmentation and Recognition Based on Improved Multi-Scale Attention Net - MDPI, https://www.mdpi.com/2076-3417/14/5/1716 34. Defect Detection in Fruits and Vegetables using K Means ... - IRJET, https://www.irjet.net/archives/V7/i4/IRJET-V7I4534.pdf
4. 35. Enhanced Leaf Disease Segmentation Using U-Net Architecture for ..., https://pmc.ncbi.nlm.nih.gov/articles/PMC12257497/
5. 36. Enhanced Leaf Disease Segmentation Using U-Net Architecture for Precision Agriculture: A Deep Learning Approach - PubMed, https://pubmed.ncbi.nlm.nih.gov/40661811/
6. 37. Feature Extraction and Segmentation Methods in Plant Disease Detection: A Multimodal Approach - ResearchGate, https://www.researchgate.net/publication/388889532_Feature_Extraction_and_Segmentation_Methods_in_Plant_Disease_Detection_A_Multimodal_Approach

7. 38. GLCM, LBP, HOG, and PHOG feature extraction analysis with ..., https://www.researchgate.net/figure/GLCM-LBP-HOG-and-PHOG-feature-extraction-analysis-with-Swedish-Leaves_tbl1_344483023
8. 39. Deep learning and content-based filtering techniques for improving plant disease identification and treatment recommendations: A comprehensive review - PMC, https://pmc.ncbi.nlm.nih.gov/articles/PMC11088271/
9. 40. Leaf Disease Classification using CNN, LSTM & RNN | Kaggle, https://www.kaggle.com/code/ghazanfarali96/leaf-disease-classification-using-cnn-lstm-rnn
10. 41. Plant Disease Detection using AI based VGG-16 Model - ResearchGate, https://www.researchgate.net/publication/360393706_Plant_Disease_Detection_using_AI_based_VGG-16_Model
11. 42. Optimizing Plant Disease Classification with Hybrid Convolutional Neural Network–Recurrent Neural Network and Liquid Time-Constant Network - MDPI, https://www.mdpi.com/2076-3417/14/19/9118
12. 43. How Convolutional Neural Networks Diagnose Plant Disease - PMC, https://pmc.ncbi.nlm.nih.gov/articles/PMC7706313/
13. 44. Early Detection of Crop Diseases Using CNN Classification - NHSJS, https://nhsjs.com/2024/early-detection-of-crop-diseases-using-cnn-classification/
14. 45. Convolutional neural network - Wikipedia, https://en.wikipedia.org/wiki/Convolutional_neural_network
15. 46. Basic CNN Architecture: A Detailed Explanation of the 5 Layers in Convolutional Neural Networks - upGrad, https://www.upgrad.com/blog/basic-cnn-architecture/
16. 47. How AlexNet Architecture Revolutionized Deep Learning - Paravision Lab, https://paravisionlab.co.in/alexnet-architecture/
17. 48. AlexNet - Wikipedia, https://en.wikipedia.org/wiki/AlexNet
18. 49. Enhanced Deep Learning Architecture for Rapid and Accurate ..., https://www.mdpi.com/2624-7402/6/1/23
19. 50. Plant Disease Classification using VGG-16: Performance ... - IJESAT, https://www.ijesat.com/ijesat/files/V23I0836_1710580381.pdf
20. 51. A Review of Popular Deep Learning Architectures: AlexNet, VGG16, and GoogleNet, https://www.digitalocean.com/community/tutorials/popular-deep-learning-architectures-alexnet-vgg-googlenet
21. 52. VGG-16 | CNN model - GeeksforGeeks, https://www.geeksforgeeks.org/computer-vision/vgg-16-cnn-model/
22. 53. user1069himanshu/Plant-disease-detection: "Plant Disease Detection" is a project that utilizes the ResNet-50 deep learning model to predict potential diseases in plants by analyzing their leaves. The model has been trained on various types of plants, including potato, tomato, corn, and more, to ensure a wide - GitHub, https://github.com/user1069himanshu/Plant-disease-detection
23. 54. Modified Resnet50 architecture for plant disease detection - ResearchGate, https://www.researchgate.net/publication/390648143_Modified_Resnet50_architecture_for_plant_disease_detection
24. 55. ahaan1984/Plant-Disease-Classification: Plant Disease ... - GitHub, https://github.com/ahaan1984/Plant-Disease-Classification

25. 56. The Basics of ResNet50 | ml-articles – Weights & Biases - Wandb, https://wandb.ai/mostafaibrahim17/ml-articles/reports/The-Basics-of-ResNet50---Vmlldzo2NDkwNDE2
26. 57. Detailed Explanation of Resnet CNN Model. | by TANISH SHARMA - Medium, https://medium.com/@sharma.tanish096/detailed-explanation-of-residual-network-resnet50-cnn-model-106e0ab9fa9e
27. 58. Plant Leaf Disease Detection by Using MobileNet and Inception - ResearchGate, https://www.researchgate.net/publication/392564277_Plant_Leaf_Disease_Detection_by_Using_MobileNet_and_Inception
28. 59. Plant Disease Detection using Inception V3 model and Particle ..., https://rifanalitica.it/index.php/journal/article/download/376/version/384/298/632
29. 60. Plant Disease Detection Using InceptionV3 - IRJET, https://www.irjet.net/archives/V9/i6/IRJET-V9I6426.pdf
30. 61. Inception (deep learning architecture) - Wikipedia, https://en.wikipedia.org/wiki/Inception_(deep_learning_architecture)
31. 62. Mastering Inception in Deep Learning - Number Analytics, https://www.numberanalytics.com/blog/ultimate-guide-inception-deep-learning
32. 63. (PDF) DenseNet Based Model for Plant Diseases Diagnosis - ResearchGate, https://www.researchgate.net/publication/363776890_DenseNet_Based_Model_for_Plant_Diseases_Diagnosis
33. 64. A Novel Deep Learning Design of Plant Disease Recognition and Detection using VGG19, ResNet50, and DenseNet169 - GRENZE Scientific Society, https://thegrenze.com/pages/servej.php?fn=38.pdf&name=A%20Novel%20Deep%20Learning%20Design%20of%20Plant%20DiseaseRecognition%20and%20Detection%20using%20VGG19,%20ResNet50,and%20DenseNet169&id=2214&association=GRENZE&journal=GIJET&year=2024&volume=10&issue=1
34. 65. PLANT DISEASE CLASSIFICATION USING DENSENET ... - JETIR.org, https://www.jetir.org/papers/JETIR2309022.pdf
35. 66. Introduction to DenseNet-121 - Kaggle, https://www.kaggle.com/code/iamtapendu/introduction-to-densenet-121
36. 67. Convolutional Networks with Dense Connectivity - Computer Science Cornell, https://www.cs.cornell.edu/~kilian/resources/DenseNet_Journal.pdf
37. 68. PlantScan: Plant Disease Detection Using MobileNet - Kaggle, https://www.kaggle.com/code/chaimaourgani/plantscan-plant-disease-detection-using-mobilenet
38. 69. LEAF DISEASE DETECTION USING MOBILENET - IRJET, https://www.irjet.net/archives/V11/i3/IRJET-V11I327.pdf
39. 70. Plant Disease Detection Project · Models · Dataloop, https://dataloop.ai/library/model/diginsa_plant-disease-detection-project/
40. 71. An illustration of MobileNet architecture to identify and classify... - ResearchGate, https://www.researchgate.net/figure/An-illustration-of-MobileNet-architecture-to-identify-and-classify-diseases_fig1_372126407
41. 72. What Is Mobilenet V2? - GeeksforGeeks, https://www.geeksforgeeks.org/computer-vision/what-is-mobilenet-v2/

42. 73. Mobilenet V2 Architecture in Computer Vision - GeeksforGeeks, https://www.geeksforgeeks.org/computer-vision/mobilenet-v2-architecture-in-computer-vision/
43. 74. (PDF) Long Short-Term Memory Recurrent Neural Networks for ..., https://www.researchgate.net/publication/359060439_Long_Short-Term_Memory_Recurrent_Neural_Networks_for_Plant_disease_Identification
44. 75. Long Short-Term Memory Recurrent Neural Networks for Plant disease Identification - Semantic Scholar, https://pdfs.semanticscholar.org/8b16/5e56f26d721bb40cf9d27132df608af656cd.pdf
45. 76. Architecture of RNN and LSTM Model · Deep Learning, https://ebetica.github.io/pytorch-Deep-Learning/en/week06/06-3/
46. 77. Introduction to Recurrent Neural Networks - GeeksforGeeks, https://www.geeksforgeeks.org/machine-learning/introduction-to-recurrent-neural-network/
47. 78. Predictions on different kinds of pests and diseases with LSTM network. - ResearchGate, https://www.researchgate.net/figure/Predictions-on-different-kinds-of-pests-and-diseases-with-LSTM-network_tbl2_326205062
48. 79. LSTMLayer - Long short-term memory (LSTM) layer for recurrent neural network (RNN) - MATLAB - MathWorks, https://www.mathworks.com/help/deeplearning/ref/nnet.cnn.layer.lstmlayer.html
49. 80. Long short-term memory - Wikipedia, https://en.wikipedia.org/wiki/Long_short-term_memory
50. 81. YOLO Object Detection Explained: Evolution, Algorithm, and Applications - Encord, https://encord.com/blog/yolo-object-detection-guide/
51. 82. The AlexNet architecture | Download Scientific Diagram - ResearchGate, https://www.researchgate.net/figure/The-AlexNet-architecture_fig3_348267694
52. 83. SerpensGate-YOLOv8: an enhanced YOLOv8 model for ... - Frontiers, https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2024.1514832/full
53. 84. YOLO Object Detection Explained: A Beginner's Guide - DataCamp, https://www.datacamp.com/blog/yolo-object-detection-explained
54. 85. (PDF) Enhanced Leaf Disease Segmentation Using U-Net Architecture for Precision Agriculture: A Deep Learning Approach - ResearchGate, https://www.researchgate.net/publication/393670462_Enhanced_Leaf_Disease_Segmentation_Using_U-Net_Architecture_for_Precision_Agriculture_A_Deep_Learning_Approach
55. 86. UNet Architecture Explained In One Shot [TUTORIAL] - Kaggle, https://www.kaggle.com/code/akshitsharma1/unet-architecture-explained-in-one-shot-tutorial
56. 87. U-Net Architecture Explained - GeeksforGeeks, https://www.geeksforgeeks.org/machine-learning/u-net-architecture-explained/
57. 88. LeafDNet: Transforming Leaf Disease Diagnosis Through Deep Transfer Learning - PMC, https://pmc.ncbi.nlm.nih.gov/articles/PMC11815709/
58. 89. Deep learning and explainable AI for classification of potato leaf diseases - Frontiers, https://www.frontiersin.org/journals/artificial-intelligence/articles/10.3389/frai.2024.1449329/full
59. 90. Plant leaf disease detection using vision transformers for precision agriculture - PMC, https://pmc.ncbi.nlm.nih.gov/articles/PMC12216567/
60. 91. Explainable AI for Plant Leaf Disease Detection: Techniques, Applications, and Future Directions - The Academic is an International Journal of Multidisciplinary Research, https://theacademic.in/wp-content/uploads/2024/08/22.pdf

61. 92. Explainable Artificial Intelligence techniques for interpretation of food datasets: a review, https://arxiv.org/html/2504.10527v1
62. 93. www.americaspg.com, https://www.americaspg.com/article/pdf/3929#:~:text=Zhang%20et%20al.,central%20server%2C%20thereby%20preserving%20privacy.
63. 94. PlantVillage Dataset - Machine Learning Datasets, https://datasets.activeloop.ai/docs/ml/datasets/plantvillage-dataset/
64. 95. PlantCLEF2025 @ LifeCLEF & CVPR-FGVC - Kaggle, https://www.kaggle.com/competitions/plantclef-2025
65. 96. Overview of PlantCLEF 2024: Multi-species Plant Identification in Vegetation Plot Images - CEUR-WS.org, https://ceur-ws.org/Vol-3740/paper-187.pdf
66. 97. Overview of PlantCLEF 2024: multi-species plant identification in vegetation plot images¿ - Les Publications du Cirad, https://publications.cirad.fr/une_notice.php?dk=613025
67. 98. PlantCLEF2022 | ImageCLEF / LifeCLEF - Multimedia Retrieval in CLEF, https://www.imageclef.org/PlantCLEF2022
68. 99. Plant Leaf Disease Detection Using Deep Learning: A Multi-Dataset Approach, https://www.researchgate.net/publication/385724578_Plant_Leaf_Disease_Detection_Using_Deep_Learning_A_Multi-Dataset_Approach
69. 100. A Lightweight and Efficient Plant Disease Detection Method Integrating Knowledge Distillation and Dual-Scale Weighted Convolutions - MDPI, https://www.mdpi.com/1999-4893/18/7/433
70. 101. New Plant Diseases Dataset - Kaggle, https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset
71. 102. Plants Diseases Detection And Classification Dataset - Google, https://toolbox.google.com/datasetsearch/search?query=diseases%20-site%3Akaggle.com
72. 103. An advanced deep learning models-based plant disease detection: A review of recent research - PMC - PubMed Central, https://pmc.ncbi.nlm.nih.gov/articles/PMC10070872/