Advances in Visual and Non-Visual Plant Disease Detection Methods: A Multi-Modal Deep Learning Perspective

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Abstract

Plant diseases pose a significant threat to global food security, underscoring the need for early, accurate, and scalable detection methods. While visual deep learning approaches—particularly convolutional neural networks (CNNs)—have demonstrated strong performance in classifying disease symptoms from leaf images, they remain limited in detecting asymptomatic infections and are sensitive to environmental variability. In contrast, non-visual techniques such as volatile organic compound (VOC) profiling, thermal imaging and spectroscopy can detect physiological changes before visual symptoms emerge. However, these methods are hindered by sensor inconsistency and a lack of standardization. This review provides a critical analysis of both visual and non-visual disease detection strategies, evaluating their accuracy, real-world applicability, and deployment challenges. Key research gaps are identified in multi-modal integration, early-stage diagnosis, and robust field-level implementation. To address these challenges, we propose a conceptual multi-modal deep learning framework that integrates CNN-based image analysis (e.g., MA-Net, MobileNet-GRU) with time-series sensor models (e.g., 1D-CNNs, LSTMs). This paper aims to lay the groundwork for next-generation plant disease diagnostic systems and outlines a forward-looking research agenda focused on sensor fusion, data alignment, and edge-enabled deployment for sustainable precision agriculture.

Keywords: Plant Disease Detection, Machine Learning (ML) and Deep Learning (DL), Visual Symptoms and Non-Visual Symptoms, Multi-Modal Fusion Strategies.

1. Introduction

In India, agriculture is central to food security and economic stability, with a large proportion of the population dependent on farming. However, plant diseases remain a major threat, causing an estimated annual crop loss of 15–25% due to pathogens, pests, and weeds (Jadhav et al., 2023). Both smallholders and commercial farms are vulnerable, underscoring the need for effective plant disease management strategies (Kumar, 2014). Traditional detection methods such as visual inspection, polymerase chain reaction (PCR), enzyme-linked immunosorbent assay (ELISA), and flow cytometry offer reliability, yet are constrained by high operational costs, lengthy processing times, and reliance on specialized expertise (Fang & Ramasamy, 2015). Recent advances in artificial intelligence (AI), machine learning (ML), deep learning (DL), and the Internet of Things (IoT) have opened pathways for scalable and real-time disease detection. Broadly, plant disease detection techniques fall into two categories: visual methods, which rely on observable symptoms, and non-visual methods, which exploit sensor-based measurements of physiological or biochemical changes. Figure 1 illustrates this taxonomy. Visual approaches, particularly convolutional neural networks (CNNs), achieve high accuracy in classifying leaf images and automating diagnosis (Khan et al., 2023). IoT-based sensor networks monitoring environmental factors such as humidity, temperature, and leaf moisture further enhance prediction capabilities (Omara et al., 2023). Yet, visual methods detect diseases only after symptoms appear, limiting preventive action (Jafar et al., 2024).

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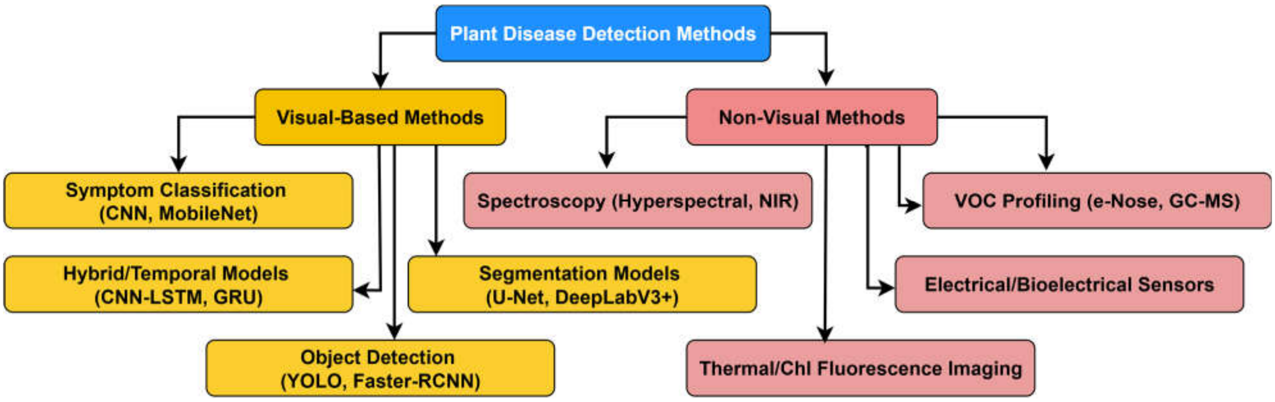

Fig 1: Taxonomy of plant disease detection methods, highlighting the classification into visual-based and non-visual sensor-based approaches.

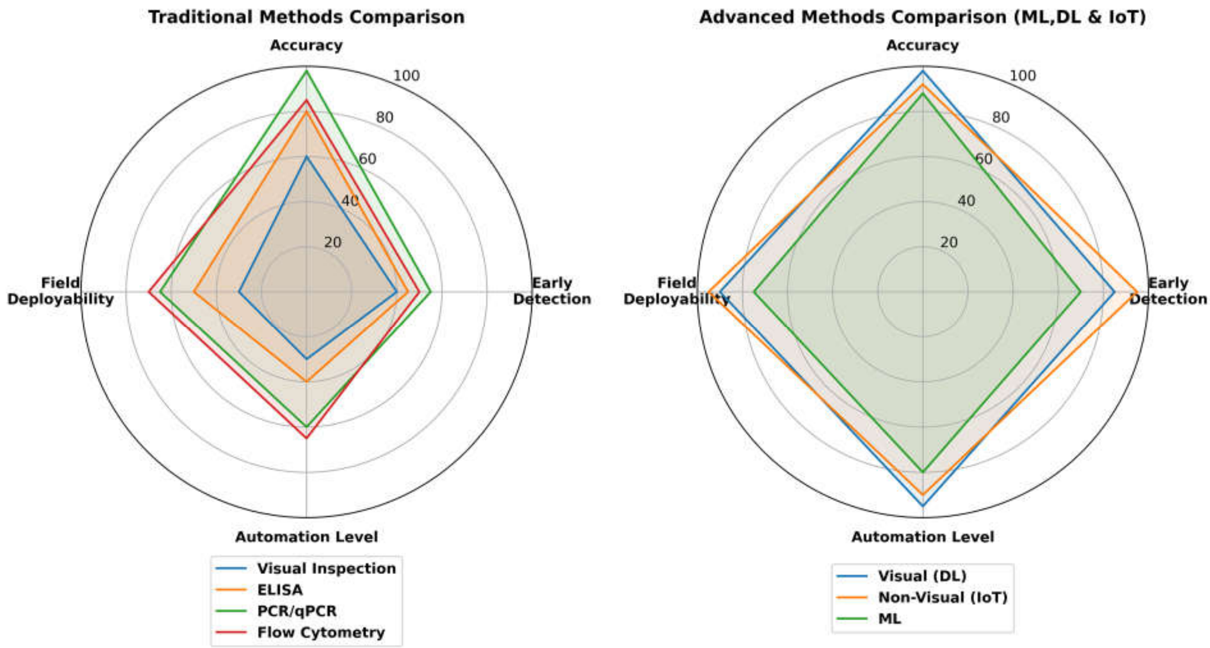

Fig 2: Comparative radar chart analysis showing performance differences between traditional methods and modern AI, ML, DL, and IoT-based plant disease detection techniques

In contrast, non-visual methods—such as volatile organic compound (VOC) profiling, spectroscopy, and hyperspectral imaging—capture pre-symptomatic biochemical changes (Sharifi & Ryu, 2018; (Mahlein et al., 2018). These systems improve early detection but face challenges including environmental sensitivity, sensor variability, and the absence of standardized frameworks for large-scale deployment (Thakur et al., 2022; Berdugo et al., 2014). Figure 2 compares traditional (Al-Rimawi et al., 2021; Prasanna et al., 2024; Sliwinska & Dolezel, 2022) and advanced detection methods (Dyussembayev et al., 2021; Yao et al., 2023; Saleem et al., 2020; Bhilare et al., 2024; Ngugi et al., 2024; Demilie, 2024; Kamilaris & Prenafeta-Boldú, 2018; Dhaka et al., 2022; Omaye et al., 2024), highlighting trade-offs in accuracy, early detection, automation, and field readiness. Recognizing the limitations of unimodal approaches, this review proposes a conceptual multi-modal deep learning framework that fuses image-based CNN models (e.g., ALAD-YOLO, MA-Net, MobileNet-GRU) with time-series sensor models (e.g., 1D-CNNs, LSTMs, GRUs). Such integration leverages both symptomatic visual cues and pre-symptomatic physiological signals, improving robustness, accuracy, and real-time deployability. While at the design stage, the framework points to future research priorities including sensor fusion optimization, cross-modal data alignment, model generalization under field conditions, and edge-compatible implementation for precision agriculture.

2. Precision Strategies for Early Detection of Plant Diseases

2.1 *Visual Analysis Techniques for Plant Disease Detection*

Visual symptoms such as leaf spots, chlorosis, wilting, and fungal lesions are primary indicators of plant diseases. However, traditional human observation is time-consuming and error-prone, particularly under field conditions (Upadhyay et al., 2025). Advances in high-resolution imaging and artificial intelligence have enabled automated visual-based detection systems that are now widely applied in plant pathology (Delfani et al., 2024). Convolutional Neural Networks (CNNs) achieve high classification accuracy from leaf images by extracting layered visual features beyond human perception. Hybrid frameworks, such as MobileNet-GRU and DSGAN2, integrate CNNs with recurrent or generative networks to enhance performance, especially with noisy or limited data. Optimization techniques like the Whale Optimization Algorithm (WOA) further improve feature selection and model robustness (Foughali et al., 2018; Khatoon et al., 2020). This section reviews visual-based detection methods, classifying existing models into symptom classifiers, segmentation models, object detectors, and hybrid pipelines. Each class is evaluated in terms of strengths, limitations, deployment readiness, and interpretability. Comparative analyses using performance metrics and scalability highlight their applicability in real-world agricultural settings.

2.1.1 Taxonomy of Visual Methods for Plant Disease Detection

The visual based plant disease detection model are categorising based on the architectural design, objectives, and processing pipeline. This taxonomy helps in understanding the applicability of the model and distinguishing different model types for various disease detection scenarios.

A. Symptom Classification Models

Symptom classification models frame plant disease detection as an image-level multi-class classification task, where each image is assigned a single disease label. These models commonly employ convolutional neural networks (CNNs) or transfer learning architectures such as MobileNet, ResNet, and DenseNet, which have shown high accuracy on benchmark datasets (Gupta & Kumar, 2020). Despite their effectiveness and relative ease of training, a major limitation is the lack of lesion localization and interpretability of learned features (Sayed et al., 2023). This section reviews representative studies, focusing on model choices, outcomes, and deployment potential.

Cucumber farming is highly vulnerable to foliar diseases that reduce both yield and quality. To tackle this, a deep convolutional neural network (DCNN) adapted from LeNet-5 was developed to classify anthracnose, downy mildew, powdery mildew, and target leaf spots. Trained on 14,208 images with augmentation and optimized using stochastic gradient descent, the model achieved 93.4% accuracy, outperforming Random Forest, Support Vector Machines, and AlexNet. Notably, it reached 98.1% accuracy for downy mildew under field-like conditions (Ma et al., 2018).

In the case of tea cultivation, manual inspection of leaf health remains a major bottleneck. Addressing this, a 16-layer CNN was trained on 5,867 leaf images collected in Tripura, India, and enhanced through augmentation. The model achieved 96.56% accuracy overall, with the highest accuracy on healthy leaves (99.10%) and the lowest on red spot disease (92%). To ensure usability, the system was supported by a RESTful API for mobile and web integration (Datta & Gupta, 2022).

For cotton production, where disease burden is especially severe in resource-constrained regions, transfer learning was employed to enhance accessibility. Several pre-trained CNNs, including VGG-16, VGG-19, InceptionV3, and Xception, were fine-tuned, with Xception achieving the best result at 98.70% accuracy. A preprocessing pipeline of normalization, contrast enhancement, and augmentation further strengthened generalization. Validation using precision, recall, and F1-score confirmed the model's robustness, and deployment was enabled through a farmer-friendly web platform (Islam et al., 2023).

In viticulture, satellite-based disease monitoring offers scalable opportunities. A custom CNN was trained on 12,000 annotated images to classify grapevine health into Healthy, Leaf Blight, Black Rot, and ESCA. The system combined TensorFlow and Google Earth Engine for processing, with a Mapbox-enabled frontend for interactive visualization. Although the model performed well, MobileNetV2 outperformed the custom CNN, achieving 99.375% accuracy, making it more suitable for lightweight monitoring (Madeira et al., 2024).

Beyond crop-specific systems, a broader benchmarking effort tested nine CNN architectures across 35 diseases and 8 plant species. Using a dataset of 30,945 images with normalization and augmentation, the study reported 100% accuracy for potato diseases using a custom 6-layer CNN. MobileNet was preferred for mobile deployment due to its compact size, while Xception demonstrated strong generalization with an F1-score of 0.992 for apple disease detection. Deployment was supported by TensorFlow Lite and a FastAPI-based backend (Rahman et al., 2025).

Table 1: Comparative Analysis of Deep Learning Architectures for Image-Based Plant Disease Symptom Classification across Multiple Crops and Modalities

Model / Study	Architecture & Backbone	Dataset / Augmentation	Accuracy / Metrics	Strengths	Limitations
Cucumber DCNN (Ma et al., 2018)	LeNet-5 variant (DCNN)	14,208 images, rotated/flipped	93.4% overall, 98.1% for Downy Mildew	Field-level performance, outperformed SVMs & AlexNet	High data requirement, less robust across environments
Tea Leaf CNN (Datta & Gupta, 2022)	16-layer custom CNN	5,867 images with various augmentations	96.56% overall, 99.1% on healthy class	Real-time API-ready, high accuracy, strong on common diseases	Geographic data bias, less effective on minority classes
Cotton Leaf (Xception) (Islam et al., 2023)	Xception (transfer learning)	Custom field images + PlantVillage	98.7% accuracy	Robust early detection, web-based inference support	Imbalanced dataset, no novel variant adaptability
Viticulture Satellite DL (Madeira et al., 2024)	Custom CNN & MobileNetV2	12,000 satellite images	99.375% (MobileNetV2)	Lightweight, scalable for satellite imagery monitoring	Dataset specificity, field generalization limited
Real-Time CNN Benchmark (Rahman et al., 2025)	VGGs, Xception, MobileNet, custom	30,945 leaf images (8 crops, 35 diseases)	100% (Potato), F1: 0.992 (Apple)	FastAPI service, quantized deployment ready	Rare diseases underrepresented, trained in controlled settings

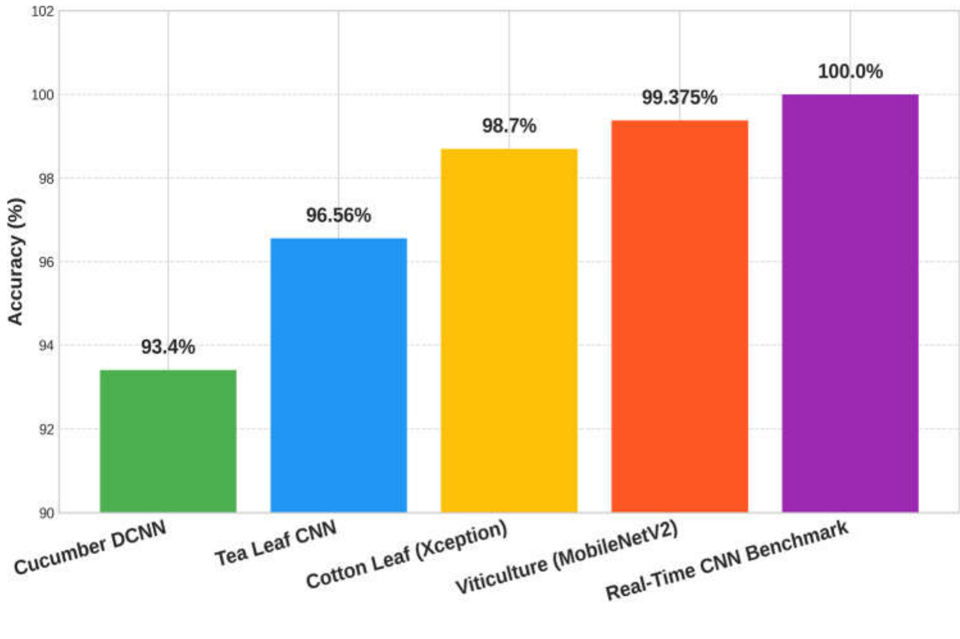

Fig 3: Accuracy Comparison of Image-Based Plant Disease Classification Models

B. Segmentation-Based Models

Segmentation-based models extend beyond simple classification by precisely identifying diseased regions at the pixel level. By leveraging architectures such as U-Net, SegNet, and DeepLabV3+, these models localize symptoms like lesions, chlorosis, or fungal growth, making them valuable for severity estimation and early-stage detection (Wang et al., 2023). Their reliance on annotated datasets, however, introduces labor-intensive labeling requirements, while their computational complexity poses challenges for real-time, edge-based agricultural applications (Chung et al., 2023). The following studies illustrate how segmentation frameworks have been adapted to improve precision in plant disease detection.

Tomato production faces frequent outbreaks of foliar diseases, and manual inspection remains both laborious and imprecise. To address this, an end-to-end semantic segmentation framework was developed using CNN-based pixel-wise labeling. Trained on PlantVillage (16,000 images) and TomatoDB (20,000 images), the model achieved 97.6% accuracy, with strong precision and recall. Beyond classification, it quantified affected leaf areas, aiding severity assessment. Despite its effectiveness, challenges such as annotation errors and limited field validation highlight the need for automated labeling and real-world trials (Khan et al., 2021).

For potato crops, RS-UNet was proposed as an improved variant of U-Net, integrating a ResNet50 encoder and Squeeze-and-Excitation attention for refined feature learning. Trained on 2,000 augmented images derived from 486 annotated samples, RS-UNet achieved an mIoU of 79.8% and a Dice coefficient of 88.86%, outperforming standard U-Net and SegNet. Its strength lay in accurately segmenting small and irregular lesions, though its generalizability to uncontrolled field environments remains limited (Fu et al., 2023).

Corn leaf diseases such as Northern Corn Leaf Blight (NCLB) demand precise lesion localization for timely intervention. NCLB-Net, an attention-boosted U-Net enhanced with VGG19 features and dual attention mechanisms (CBAM and SE), was introduced to meet this need. With additional receptive field blocks for multi-scale context capture, the model achieved 92.43% mIoU and 94.71% pixel accuracy on a dataset of 20,897 augmented images. Despite strong robustness under real-field conditions, its computational demands pose barriers to lightweight deployment (Mu et al., 2024).

Apple orchards benefit from precise lesion segmentation, particularly when multiple diseases co-occur. To support this, an improved Multi-Scale Attention Network (MA-Net) was designed using a Mix Vision Transformer encoder and Effective Channel Attention. Applied to an augmented dataset of 21,099 images, it achieved 98.1% mIoU and 99.6% accuracy, outperforming U-Net and DeepLabV3+. While highly accurate, reliance on extensive annotation and limited field validation remain key challenges for scaling (Yang et al., 2024).

In maize, SE-Swin Unet was introduced as an advanced architecture for segmenting foliar diseases such as large spot, small spot, and stripe rust. By inserting Squeeze-and-Excitation blocks into skip connections, the model emphasized lesion features while suppressing background noise. Trained on 800 annotated images, it achieved 84.61% mIoU and 89.91% F1-score, surpassing conventional CNN-based baselines. However, its high computational cost increases inference time, underscoring the need for compression techniques for real-time field use (Yang et al., 2024).

For tomato leaf diseases, where small and blurred lesions are common, MC-UNet was developed with multi-scale convolution, cross-layer attention, and SoftPool modules. Trained on 6,372 images, it achieved 91.32% accuracy and 88.42% mAP, outperforming U-Net and DeepLabV3. Visual analysis confirmed improved localization of tiny lesions, although performance declined in complex field backgrounds. Future directions include background-aware training and multistage segmentation for greater robustness (Deng et al., 2023).

Table 2: Comparative Analysis of Segmentation-Based Deep Learning Models for Plant Disease Symptom Localization and Classification

Model	Backbone / Enhancements	Dataset / Size	Accuracy / mIoU	Strengths	Limitations
Deep Semantic Segmentation (Tomato) (Khan et al., 2021)	CNN + ReLU + MaxPooling + Softmax	PlantVillage + TomatoDB / 36,000	97.6% Accuracy	High lesion quantification accuracy	No field validation
RS-UNet (Potato) (Fu et al., 2023)	ResNet50 + SE block	486 samples → 2,000 (aug.)	79.8% mIoU / 88.86% Dice	Strong on small/irregular lesions	Controlled dataset, generalization
NCLB-Net (Corn) (Mu et al., 2024)	U-Net + VGG19 + CBAM + SE + RFB	2,419 samples → 20,897 (aug.)	92.43% mIoU / 94.71% Pixel Acc.	High field robustness, custom loss	Computationally heavy
MA-Net (Apple) (Yang et al., 2024)	MiT + ECA + MA-Net	2,029 → 21,099 (aug.)	98.1% mIoU / 99.6% Accuracy	Best accuracy with lightweight encoder	Manual annotation burden
SE-Swin Unet (Maize) (Yang et al., 2024)	Swin-Unet + SE blocks	800 annotated (aug.)	84.61% mIoU / 92.98% Accuracy	Handles complex lesion patterns well	High FLOPs, slower inference
MC-UNet (Tomato) (Deng et al., 2023)	UNet + MCM + CAFM + SoftPool	6,372 images (aug.)	91.32% Accuracy / 88.42% mAP	Lightweight, effective under variation	Field generalization underperforms

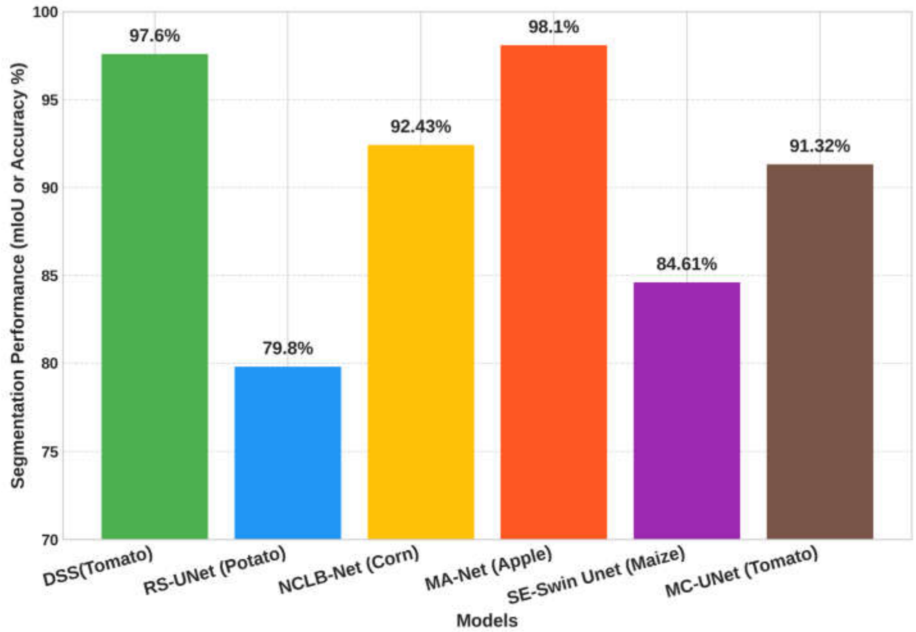

Fig 4: Segmentation Performance Comparison of Deep Learning Models for Plant Disease Symptom Localization

Comparative analysis (Table 2, Figure 4) indicates that MA-Net achieves the highest segmentation accuracy with strong computational efficiency, while NCLB-Net demonstrates robust adaptability under field conditions. MC-UNet balances accuracy and efficiency, making it suitable for edge deployment, whereas Deep Semantic Segmentation and RS-UNet achieve high accuracy but require broader validation. In conclusion, MA-Net stands out for precision, while MC-UNet provides the best trade-off for practical, real-time deployment.

C. Object Detection Pipelines

Object detection frameworks provide coarse yet efficient localization of multiple disease symptoms within complex agricultural scenes. By drawing bounding boxes around diseased regions, they enable rapid identification across leaves and crops, balancing accuracy with computational speed. Popular architectures such as YOLOv5, SSD, and Faster R-CNN have gained traction for their ability to operate in real-time and at scale (Suryawati et al., 2024). These pipelines are well suited for mobile and UAV-based systems that demand speed and adaptability, though they remain vulnerable to occlusion, inconsistent illumination, and overlapping lesions. The following studies illustrate their adaptation to diverse crops and field conditions (Zhang et al., 2022).

Apple orchards often present overlapping leaves and variable lighting, which complicates visual disease detection. To address this, BTC-YOLOv5s was developed by enhancing YOLOv5s with a BiFPN for multi-scale feature fusion, a Transformer Encoder for global context, and CBAM attention for spatial refinement. Trained on 2,099 annotated images containing 10,727 lesions, the model reached 84.3% mAP@0.5 and an F1-score of 80.56%, surpassing YOLOv4-tiny, SSD, and Faster R-CNN. It maintained real-time performance at 8.7 FPS on CPU and remained robust under blur, low light, and symptom overlap. Nonetheless, detection performance declined for rare diseases and severe occlusion, requiring further dataset balancing (Li et al., 2023).

Monitoring large-scale crops requires airborne solutions that overcome ground-level limitations. MCD-YOLOv5 was designed for UAV-based detection of multiple rice diseases, integrating Multi-Layer Feature Fusion, CBAM, and a Detection Transformer to enhance multi-symptom recognition. UAVs equipped with infrared sensors and 5G modules collected imagery, which was combined with PlantVillage data to form a nine-class hybrid dataset. The model achieved 97.52% accuracy, 94.43% mAP, and inference speeds of 0.74 ms, outperforming Faster R-CNN, SSD, and YOLOv5 baselines. While effective for scalable monitoring, model performance was less consistent under variable lighting and complex field backgrounds, highlighting the need for improved generalization strategies (Li et al., 2023).

Detecting apple leaf diseases in natural orchards is hindered by small lesion sizes and overlapping symptoms. An enhanced Faster R-CNN framework tackled this challenge using Res2Net-50 with Feature Pyramid Networks for feature extraction, RoIAlign pooling for precision, and Soft-NMS to reduce false positives. Trained on the AALDD dataset of 4,182 orchard images across five diseases, it achieved 63.1% mAP, with outstanding AP50 values for powdery mildew (98.9%) and mosaic (94.1%). Though slower at 12.2 FPS compared with one-stage detectors, the system excelled in identifying dense, fine-grained lesions. Its trade-off between speed and accuracy limits real-time use but improves reliability in precision agriculture (Gong & Zhang, 2023).

Data scarcity often limits robust model training for crop disease detection. To overcome this, a CycleGAN-based augmentation strategy was combined with DenseNet-enhanced YOLOv3 to improve detection of apple anthracnose lesions. Synthetic images increased dataset diversity, while DenseNet improved feature reuse. Trained on 512×512 resolution data and evaluated on 50 real-world images, YOLOv3-Dense achieved an F1-score of 0.816, IoU of 0.917, and 31 FPS inference speed. The approach proved robust under small lesion conditions and complex illumination. However, challenges persist in extending the method to multiple disease types and maintaining performance when image quality is degraded (Tian et al., 2018).

Lightweight detection models are crucial for deployment on mobile and edge devices in agriculture. ALAD-YOLO addressed this by refining YOLOv5s with MobileNetV3s, GhostNet-based DWC3 modules, and a group convolution–driven SPPCSPC_GC layer, supported by Coordinate Attention for spatial learning. Trained on 2,748 annotated apple leaf images under variable conditions, it achieved 90.2% mAP@0.5–0.95, 98.7% mAP@0.5, and required only 6.1 GFLOPs. Compared with YOLOv5s, it improved accuracy while reducing computation by 9.7 GFLOPs. While slightly less precise on small occluded targets, its efficiency makes it well suited for edge deployment in resource-constrained agricultural systems (Xu & Wang, 2023).

Complex field conditions with occlusion and clutter demand more advanced detection strategies. YOLOv7-PSAFP was proposed to meet this need, augmenting the YOLOv7 backbone with a Progressive Spatial Adaptive Feature Pyramid and Adaptive ELAN modules for robust feature fusion. Varifocal Loss and Loss Rank Mining further addressed class imbalance. Evaluated on PlantVillage and rice–corn pest datasets, it achieved mAP@0.5 scores of 84.7% and 93.3%, outperforming

YOLOv7, YOLOv8, and Faster R-CNN. Its strength lay in capturing subtle disease features and reducing false positives. However, high computational demand restricts mobile deployment, motivating future work in lightweight compression (Du et al., 2024).

Table 3: Comparative Analysis of Model Architectures, Datasets, and Performance Metrics in Object Detection Pipelines for Plant Disease Detection

Model	Architecture Enhancements	Dataset / Size	mAP / Accuracy / Speed	Strengths	Limitations
BTC-YOLOv5s (Apple) (Li et al., 2023)	BiFPN + Transformer + CBAM	2,099 images / 10,727 lesions	84.3% mAP@0.5 / 8.7 FPS (CPU)	Robust under occlusion, motion blur, lighting issues	Lower performance on rare diseases
MCD-YOLOv5 (UAV-based) (Li et al., 2023)	MLFF + CBAM + Detection Transformer	UAV + PlantVillage hybrid (rice)	94.43% mAP / 0.74 ms prediction	UAV-scalable, high-speed multi-disease detection	Generalization under lighting complexity
Improved Faster R-CNN (Apple) (Gong & Zhang, 2023)	Res2Net-50 + FPN + Soft-NMS + RoIAlign	AALDD (4,182 field images)	63.1% mAP / 12.2 FPS	Accurate for overlapping lesions, high AP for diseases	Slower than single-stage detectors
YOLOv3-Dense (Apple) (Tian et al., 2018)	DenseNet + CycleGAN augmentation	512×512, 50 test field images	0.917 IoU / 31 FPS / F1: 0.816	GAN-augmented robustness, fast real-time detection	High image acquisition demand, generalization
ALAD-YOLO (Apple) (Xu & Wang, 2023)	YOLOv5s + MobileNetV3 + GhostNet + CoordAttention	2,748 images	98.7% mAP@0.5 / 90.2% mAP@0.5–0.95	Extremely lightweight (6.1 GFLOPs), mobile deployable	Minor drop in precision under occlusion
YOLOv7-PSAFP (Crop-Pest) (Du et al., 2024)	YOLOv7 + PSAFP + AELAN + VFL + LRM	Filtered PlantVillage + Rice-Corn	84.7%–93.3% mAP@0.5	Excels under cluttered scenes and occlusions	High compute cost, not mobile-optimized

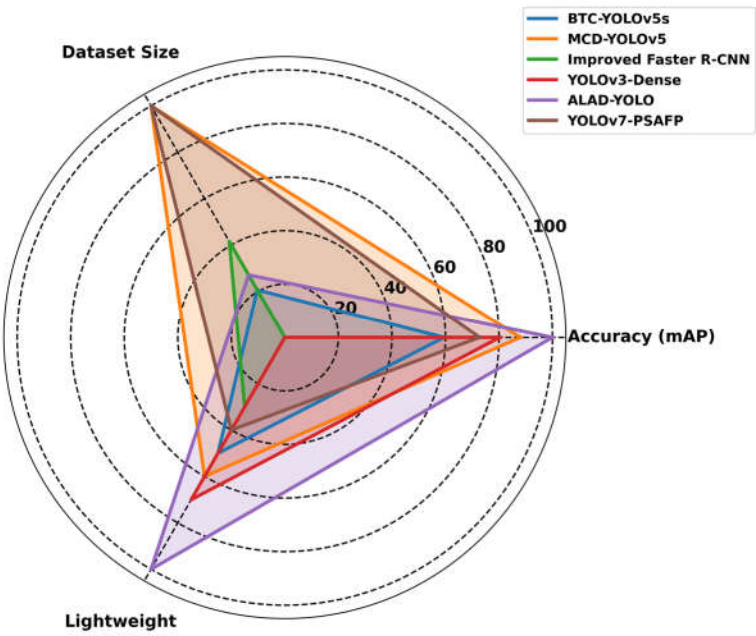

Fig 5: Radar Chart Comparison of Object Detection Pipelines across Accuracy, Dataset Size, and Lightweight Deployment Suitability

Comparative analysis (Table 3, Figure 5) reveals that MCD-YOLOv5 balances speed and accuracy for UAV-based monitoring, while ALAD-YOLO offers superior accuracy with low computational cost for edge deployment. YOLOv7-PSAFP and BTC-YOLOv5s excel in cluttered environments, whereas Improved Faster R-CNN and YOLOv3-Dense provide reliable field performance at higher resource demands. In conclusion, ALAD-YOLO emerges as the most practical solution for efficient, real-time agricultural deployment.

D. Hybrid and Temporal Models

Hybrid and temporal models integrate convolutional neural networks (CNNs) with additional components such as recurrent neural networks (RNNs), optimization algorithms, or external sensor streams. This class of models is designed to capture both spatial patterns (from images) and temporal or contextual dynamics (e.g., disease progression over time or sensor fluctuations). Examples include MobileNet-GRU, CNN-LSTM, and ANN with optimization layers such as the Whale Optimization Algorithm (WOA) (Kanakala & Ningappa, 2025). These models often demonstrate superior performance in noisy or imbalanced datasets. However, they are more complex to train, require high computational resources, and are less interpretable, limiting their direct deployment in resource-constrained environments (Jahin et al., 2025). The following summaries cover key studies under the category of hybrid and temporal models, which combine spatial, temporal, and optimization strategies to enhance plant disease detection in dynamic agricultural conditions.

Grapevine cultivation is highly vulnerable to foliar diseases, necessitating early and accurate detection for yield protection. This study proposes a hybrid IoT and supervised machine learning framework that integrates environmental sensing with predictive analytics for grape disease monitoring. Real-time data on temperature, humidity, and leaf wetness were collected to train classification models using a self-generated dataset of 10,000 records. The system achieved 98.25% accuracy for powdery mildew, 98.85% for downy mildew, and 93.95% for bacterial leaf spot. While effective, limitations include sensor calibration errors, cloud-processing delays, and limited scalability, highlighting the need for edge-enabled, adaptive viticulture solutions (Gawande et al., 2024).

Olive cultivation is severely affected by foliar diseases, requiring advanced diagnostic systems for timely intervention. This study presents a hybrid deep learning framework that integrates Artificial Neural Networks (ANNs) with Whale Optimization Algorithm (WOA) for feature selection and classification. A dataset of 3,300 images of healthy and diseased olive leaves was analyzed, where Gray Level Co-occurrence Matrix (GLCM) features were optimized using WOA to reduce dimensionality and improve convergence. A Feed-Forward Neural Network (FFNN), trained with the Levenberg–Marquardt algorithm, achieved 98.4% accuracy, outperforming Naïve Bayes, KNN, and SVM. Despite strong performance, dataset limitations and lack of real-world validation remain (Alshammari et al., 2023).

Okra cultivation is severely impacted by Yellow Vein Mosaic Virus (YVMV), necessitating rapid and accurate diagnostic solutions. This study introduces a MobileNet-GRU hybrid model that leverages MobileNet for lightweight spatial feature extraction and a Gated Recurrent Unit (GRU) for sequential pattern learning. Implemented using the Keras Sequential API, the architecture comprises dense layers (512 ReLU units), a GRU layer (128 units), and a softmax classifier. The model achieved 99.27% accuracy with a binary cross-entropy loss of 0.02, outperforming ResNet50, InceptionV3, VGG19, and EfficientNet. Despite strong results, limited dataset variability and hardware constraints hinder generalization and real-time deployment (Chawla et al., 2024).

Tomato plants are highly susceptible to destructive foliar diseases such as gray loose leaf infection and late blight, necessitating accurate early detection frameworks. This study introduces a hybrid deep learning approach integrating Principal Component Analysis (PCA) for dimensionality reduction with Improved Quantum Whale Optimization (IQWO) for hyperparameter tuning, including dropout rates, convolutional filter sizes, and training epochs. A deep neural network (DNN), evaluated on the PlantVillage dataset, achieved 97.46% accuracy using a K-Nearest Neighbors (KNN) classifier, outperforming AlexNet, VGG16, ResNet50, and DenseNet121. Despite strong performance, computational overhead and lack of field validation remain challenges, requiring adaptive edge-enabled solutions (Sowmiya & Krishnaveni, 2023).

Rice production is highly vulnerable to foliar diseases, requiring precise and scalable diagnostic frameworks. This study proposes a deep hybrid model integrating a Deep Spectral Generative Adversarial Network (DSGAN2) with Improved Artificial Plant Optimization (IAPO) for early rice leaf disease detection. The pipeline incorporates an Improved Threshold Neural Network (ITNN) for image enhancement, Segment Multiscale Neural Slicing (SMNS) for fine-grained segmentation, and Spectral Scaled Absolute Feature Selection (S2AFS) for targeted feature extraction, optimized via Social Spider Optimization (S2O-FCW). Trained on 10,080 images, the model achieved 98.8% accuracy, surpassing APS-DCCNN, AlexNet, and CNN baselines, though limited by dataset diversity and computational demands (Mahadevan et al., 2024).

Hill banana cultivation is highly susceptible to diseases such as bunchy top and sigatoka leaf spot, necessitating early and automated diagnostic frameworks. This study presents an IoT-driven model that integrates image analysis with environmental sensing through wireless sensor networks (WSN). The pipeline involves Raspberry Pi3-based image acquisition, grayscale conversion, histogram equalization, k-means clustering for segmentation, and Gray Level Co-occurrence Matrix (GLCM) feature extraction. Environmental parameters—temperature, humidity, and soil moisture—are monitored via DHT22 and KG003 sensors and processed in a cloud repository. Random Forest classification achieved 99% accuracy, surpassing k-NN, though limitations in segmentation reliability and deep learning adaptability remain (Devi et al., 2019)

This study presents a Cloud-IoT-enabled Decision Support System (DSS) for real-time management of Phytophthora infestans in crops, offering an alternative to conventional weather station-based models via localized microclimate sensing. Waspmote sensor nodes measure temperature, humidity, and leaf wetness, transmitting data through ZigBee XBee 802.15.4 to a Meshlium IoT gateway supporting WiFi, ZigBee, and 3G/GPRS. Data is relayed to the Ubidots cloud via MQTT, while the SIMCAST prediction model issues preventive alerts and fungicide recommendations when blight risk exceeds 30 units. Field trials confirm accurate, timely intervention. Future enhancements include deep learning (RNNs, LSTMs), hyperspectral pathogen detection, and LoRaWAN/NB-IoT integration (Foughali et al., 2017).

This study presents an IoT-integrated deep learning framework for early detection of tomato plant diseases, leveraging Improved Quantum Whale Optimization with PCA (IQWO-PCA) for enhanced model efficiency and classification accuracy. PCA reduces feature dimensionality, followed by deep feature extraction using pretrained networks (AlexNet, VGG16, ResNet50, DenseNet121). Hyperparameters are optimized via random search, while comparative analysis against LDA, KNN, Decision Trees, and Naïve Bayes shows KNN achieves 97.46% accuracy. IoT sensors provide real-time environmental data for context-aware predictions. Challenges include limited dataset variability, computational overhead, and sensor noise. Future work emphasizes dataset expansion, robust field deployment, and scalable real-time monitoring (Cardoso et al., 2022).

Table 4: Comparative Analysis of Hybrid and Temporal Models for Plant Disease Detection

Model / Study	Architecture & Backbone	Dataset / Augmentation	Accuracy / Metrics	Strengths	Limitations
IoT-Based Smart Agriculture (HANN + AMRO) (Ara et al., 2024)	Hybrid ANN with GoogleNet layers, K-means clustering, AMRO for routing	Sensor-based real-time data; NS-2 simulated	95% Accuracy, PDR: 95%, Throughput: 92.4kbps, Latency: 0.07 ms	High accuracy, energy-efficient, optimized routing	Cloud dependency, high complexity, not validated on field scale
Deep Residual Network with CHGCSO (Saini et al., 2025)	DRN with handcrafted features (HoG, SLIF, LTP) and CHGCSO for optimization	Field sensor images;median filtering for preprocessing	94.3% Accuracy, F1-score: 93%, Sensitivity: 93.3%	Robust under noisy conditions, optimized feature refinement	Model complexity, limited scalability, cloud reliance
Grape Disease Detection using ML + IoT (Gawande et al., 2024)	Classical ML (non-DL); environmental sensor fusion	10,000-record self-collected dataset; sensor-driven features	98.85% (downy mildew), 98.25% (powdery mildew)	High accuracy, real-time alerts, interpretable	Sensor calibration errors, lacks DL, cloud-dependent
ANN with Whale Optimization (WOA)	FFNN + WOA-enhanced GLCM	3,300 olive leaf images; no	98.4% Accuracy; high precision,	Efficient feature selection, low	Small dataset, no IoT or real-time

(Alshammari et al., 2023)	feature selection	augmentation stated	recall, specificity	false rates	deployment
MobileNet-GRU for Okra YVMV Detection (Chawla et al., 2024)	MobileNet CNN for spatial, GRU for temporal learning	Okra leaf image dataset; no augmentation stated	99.27% Accuracy, Binary loss: 0.02	Lightweight, temporal sensitivity, outperforms ResNet & VGG	Dataset limitations, not tested in field, hardware optimization needed
Tomato Disease Detection with IQWO-PCA (Sowmiya & Krishnaveni, 2023)	DNN with PCA for dimensionality reduction, IQWO for hyperparameter tuning	PlantVillage dataset; no real-time images	97.46% Accuracy, Precision: 96.23%	Efficient tuning, feature compression, high generalization	Overfitting risk, lacks field testing, complex tuning
Rice Disease Detection with DSGAN2 + IAPO (Mahadevan et al., 2024)	GAN-based model with segmentation (SMNS), optimization (S2O-FCW)	10,080 rice leaf images; image enhancement used	98.8% Accuracy, 40.8% reduction in false positives, 98 ms processing	Advanced segmentation, high speed, GAN-generated robustness	High overhead, complex pipeline, limited real-world validation
IoT-Enabled DNN (LDEDLP Framework) (Ramkumar et al., 2021)	DNN with HSV segmentation, IoT sensing, cross-validation	54,300 images (PlantVillage); HSV color-based preprocessing	99% Accuracy, enhanced region segmentation	Real-time alerts, scalable dataset, strong validation	Sensitive to image quality, computationally heavy, segmented input needed
IoT-Driven Image and Sensor-Based Disease Detection in Hill Banana (Devi et al., 2019)	Random Forest classifier with GLCM-based image features and k-means segmentation	Field-collected banana leaf images; no DL used	99% Accuracy; outperforming k-NN	Combines WSN and image analysis, low-cost sensing	Sensitive to lighting/angle variation; lacks CNN features
Early Blister Blight Prediction in Tea Using IoT + MLR (Liu et al., 2022)	Multiple Linear Regression (MLR) based on environmental predictors	Five-year historical climatic dataset (2015–2019)	91% Accuracy; rainfall negatively correlated	Simple, explainable, long-term validation	Linear model limits adaptability to non-linear patterns
Edge-AI for In-Field Black Sigatoka Detection in Banana (Figorilli et al., 2025)	Custom 8-layer CNN with dropout; Android edge app with Camera2 API	408 images across 6 BSD severity classes	78% Validation Accuracy, F1 = 0.98 (Class 5)	Portable, offline inference, fine-grained class detection	Small dataset, limited accuracy for intermediate severity
IoT Crop Monitoring with MELM Classifier (Balram & Kiran Kumar, 2022)	Multi-hidden Layer Extreme Learning Machine (MELM) with color/morphological features	VGA camera leaf images; Otsu, K-means for segmentation	99.12% Accuracy; DSC, SSIM for segmentation validation	Strong segmentation + classification combo, high precision	Manual annotation needed; environmental noise sensitivity
IoT-GPU Framework for Smart Pest and Disease Control (Gomathy Nayagam et al., 2023)	CNN + Reinforcement Learning; GPU parallel simulation	Hyperspectral & sensor data; vegetation indices (GNDVI, VARIrededge)	98.65% Accuracy; 30% faster than CPU models	High-speed processing, adaptive control logic	High hardware cost; inaccessible to low-resource farms
Cloud-IoT Decision Support System with SIMCAST (Foughali et al., 2017)	SIMCAST-based rule model using microclimate sensing and XBee modules	Ubidots cloud platform; ZigBee & Waspmote nodes	Timely disease alerts; field trial–validated	Low-cost, scalable, fungicide optimization enabled	Lacks AI/ML features; relies on connectivity and thresholds
Quantum Whale DRDNN for Tomato Disease Detection (Cardoso et al., 2022)	IQWO-PCA optimized DNN with KNN classifier; DL feature extraction (AlexNet, VGG16, etc.)	Tomato leaf image dataset; PCA for dimensionality reduction	97.46% Accuracy (KNN), better than LDA, DT, NB	Deep features + IoT sensing; strong classifier performance	Dataset variability limited; field deployment untested

As summarized in Table 4 and Figure 6, IoT-integrated deep learning and optimization models achieve 94.3–99.27% classification accuracy, with MobileNet-GRU (99.27%) and MELM (99.12%) being suitable for real-time, resource-constrained environments. Metaheuristic optimizations (WOA 98.4%, IQWO 97.46%) improve accuracy but increase computational demand. Limited dataset sizes (408–3,300 images) restrict generalizability, highlighting the need for scalable, field-validated AI frameworks for reliable agricultural disease detection.

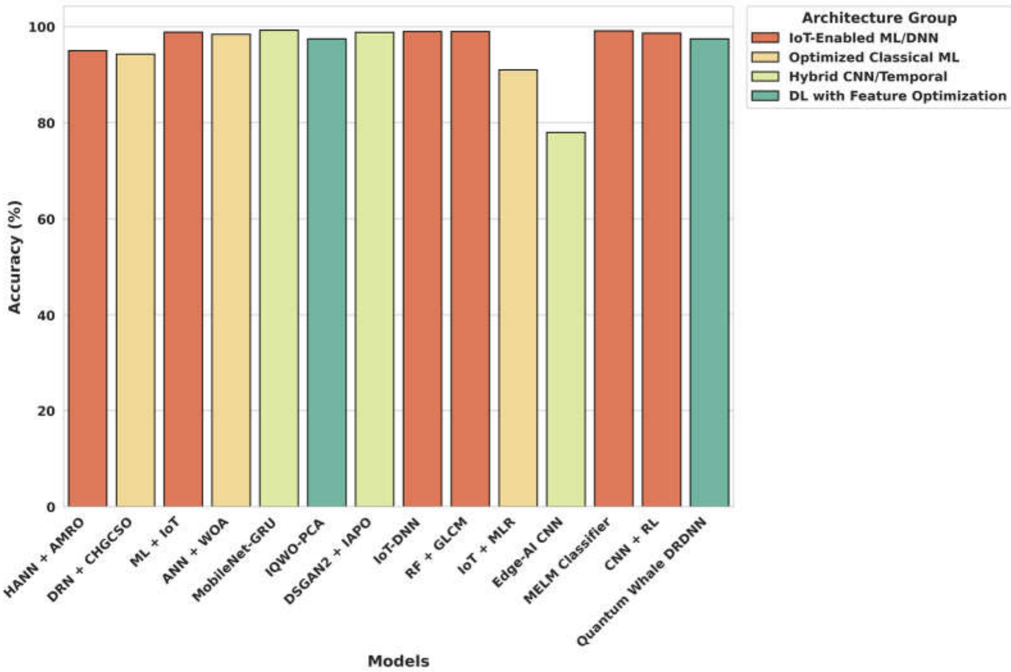

Fig 6: Accuracy Comparison of Hybrid and Temporal Models Grouped by Architecture Type

2.2 Non-Visual Sensing Techniques

Non-visual biomarkers represent crucial physiological and biochemical changes in plants that often precede visible symptoms, enabling early disease detection and timely intervention. These biomarkers can be categorized based on the underlying sensing modality, including: (i) volatile organic compounds (VOCs) emitted during pathogen attack or stress; (ii) thermal and fluorescence-based responses linked to changes in transpiration and photosynthetic efficiency; (iii) bioelectrical or impedance signals associated with root health; and (iv) biochemical shifts such as enzyme activity or secondary metabolite production (Venbrux et al., 2023; Castro-Moretti et al., 2020). Advanced sensing platforms—ranging from e-noses and gas chromatography to MEMS biosensors, thermal imaging, and soil-based electrochemical probes—facilitate the capture of these subtle signals (Buja et al., 2021; Jayapalan & Ananth, 2023). To extract meaningful features from these modalities, machine learning (ML) and deep learning (DL) techniques such as CNNs, LSTMs, and hybrid models are employed, particularly for classifying time-series or spectral data (Roper et al., 2021; John et al., 2023). This section critically reviews the key contributions in non-visual plant disease detection, focusing on sensor design, data preprocessing, learning models, deployment feasibility, and current challenges in scalability and integration.

Table 5 presents a structured taxonomy of key non-visual sensing modalities used in plant disease detection. These techniques vary widely in their target biomarkers, stress types addressed, and data characteristics, necessitating distinct preprocessing and machine learning pipelines. For example, while VOC sensors offer early detection capabilities by capturing metabolic emissions, they are often sensitive to environmental fluctuations and require frequent calibration. In contrast, thermal imaging provides a passive method to monitor physiological stress like stomatal closure but may be affected by sunlight and background heat. Similarly, electrical impedance sensing is valuable for monitoring root-level disruptions but can suffer from soil interference. As shown in the table, each sensing modality is paired with typical machine learning models (e.g., CNN, SVM, LSTM) based on the nature of the captured signal—whether spectral, thermal, or analogy (A, 2023). This taxonomy lays the foundation for the critical review that follows, enabling a structured comparison of techniques based on their detection scope, technical demands, and deployment readiness.

Table 5: Taxonomy of Non-Visual Plant Disease Detection Techniques

Sensor Type	Target Biomarker	Stress Type	Data Type	ML Model Used	Strengths	Limitations
VOC Sensors (e-nose, GC-MS) (Ratnayake et al., 2024)	Ethylene, alcohols, aldehydes	Biotic (Fungal/Bacterial)	Time-series spectra	SVM, Discriminant Analysis	Early detection, portable sensing, fast screening	Cross-sensitivity, environmental influence
Thermal Imaging (Zubler & Yoon, 2020)	Leaf surface temperature	Abiotic (Drought, Stress)	Thermal map (image)	Random Forest, LSTM	Passive, real-time, scalable for large fields	Sensitive to sunlight, canopy structure
Chlorophyll Fluorescence (Moustaka & Moustakas, 2023)	Photosynthetic disruption (ChlF signals)	Biotic/Abiotic	Fluorescence indices	ANN, SVM	Early-stage detection, non-invasive, high sensitivity	Affected by light angle, plant species variability
Electrical Impedance (Simmi et al., 2020)	Xylem blockage, root cell disruption	Root infections (Biotic)	Time-series voltage fluctuations	Time-series classifiers, Entropy-based features	Sensitive to systemic stress responses, early root infection detection	Soil salinity/ moisture interference, setup complexity
MEMS/ Nanosensors (Leong et al., 2022)	Enzyme activity, disease-specific metabolites	Biotic (Viral/Fungal)	Analog biosignal	CNN, Hybrid DL	High specificity, potential for wearables, rapid detection	Limited field deployment data, power/communication issues
Multispectral/ NIR Sensors (Berger et al., 2022)	Pigments, water content, canopy structure	Abiotic (Heat, Drought, Nutrient Deficiency)	Spectral signature (VIS-NIR-SWIR)	PCA+SVM, CNN, Random Forest	Sensitive to physiological stress, integrable with UAVs	High cost, calibration demands, bulkiness

Non-destructive Vis/NIR spectral sensing offers a robust alternative to destructive biochemical assays for real-time banana quality assessment. In Philippine Cavendish bananas, a 12-channel Vis/NIR system was employed to estimate soluble solid content (SSC), pH, and firmness (FM) through spectral reflectance analysis. Preprocessing techniques such as mean centering, multiplicative scatter correction (MSC), and successive projections algorithm (SPA) enhanced signal quality and minimized multicollinearity. Regression-based models, including Multiple Linear Regression (MLR), Partial Least Squares (PLS), and Backpropagation Neural Networks (BPNN), were compared, with the Flexible Spectral Classification (FSC) algorithm achieving 97.5% accuracy. Real-time deployment utilized ESP32 microcontrollers, ONENET cloud, and e-paper displays, though spectral overlap and reduced FM/pH prediction accuracy remain challenges (Wang et al., 2022).

Fluorescent array-based sensing provides a portable and low-cost alternative to molecular diagnostics for rapid fungal pathogen detection in crops. A smartphone-integrated fluorescent sensor array was developed to identify *Penicillium italicum*, *Alternaria alternata*, and *Fusarium sacchari* through metabolic fluorescence profiling in lemon fruits. The system employs multiple organic fluorophores generating unique emission patterns under 365 nm UV excitation, captured by a smartphone camera in a dark chamber. Using Partial Least Squares Discriminant Analysis (PLS-DA), detection limits of 1.7–2.0 × 10^3 conidia/mL were achieved for *P. italicum*. While highly portable and fast, challenges include reduced sensitivity compared to qPCR and reproducibility under complex conditions (Santonocito et al., 2023).

Hybrid multimodal sensing platforms are advancing real-time, non-invasive crop health monitoring. PlantFit integrates electrochemical sensors for salicylic acid (SA) and ethylene (ET) with physical sensors measuring vapor pressure deficit (VPD), temperature, humidity, pressure, and radial stem strain. Mounted on leaves and stems, it continuously tracks biotic and abiotic stress biomarkers in tomato, cabbage, and bell pepper. Data are acquired via ESP32 with IoT-enabled wireless transmission.

Multi-crop trials showed strong correlations (Pearson $r > 0.92$), with SA sensitivity of 0.00226 μM^{-1} (LOD: 0.644 µM) and ET sensitivity of 17.073 µA/log(ppm) (LOD: 0.6089 ppm). Recalibration needs and environmental instability remain challenges (Hossain & Tabassum, 2023).

Biomimetic plant wearables offer a novel, non-invasive approach to high-fidelity stem growth monitoring for crop health assessment. The Integrated Plant Wearable System (IPWS) employs an Adaptive Winding Strain (AWS) sensor inspired by tendril morphology, ensuring secure yet stress-free adhesion to stems. Constructed with a laser-induced graphene (LIG) serpentine structure embedded in Ecoflex, it enables precise micro-strain detection with minimal drift and a thermal coefficient of 0.17 $°C^{-1}$. Wireless transmission via ESP32 and Wi-Fi supports real-time smartphone visualization. Tomato trials demonstrated performance comparable to commercial LVDTs, though limitations include crop compatibility, Wi-Fi dependence, and lack of predictive analytics (Zhang et al., 2022).

VOC-based biosensing provides a sensitive, non-invasive strategy for early pathogen detection in citrus. A GC–MS-integrated biosensor system was developed to identify *Penicillium digitatum* infection in *Citrus sinensis* using bioluminescent *E. coli* bioreporters engineered to respond to oxidative, cytotoxic, genotoxic, and quorum-sensing VOC shifts. Controlled inoculation trials showed detectable bioluminescence changes three days post-infection, preceding visible symptoms. This platform enables real-time, portable disease monitoring for postharvest applications. While highly sensitive, limitations include environmental VOC interference, cross-reactivity, and calibration drift. Future work should emphasize biosensor miniaturization, VOC pattern recognition with machine learning, and automated supply-chain integration (Chalupowicz et al., 2020).

VOC profiling combined with machine learning offers a promising approach for early detection of *Botrytis cinerea* in grapes. Using solid-phase microextraction (SPME) and GC–MS, VOCs from artificially inoculated Sangiovese and Corvina grape cultivars were analyzed over five days. Partial Least Squares Discriminant Analysis (PLS-DA) identified green leaf volatiles (GLVs)—including hexanol, 2-hexen-1-ol, 3-hexen-1-ol, and 1-penten-3-ol—as key biomarkers of infection. Postharvest dehydration significantly influenced VOC expression, revealing varietal and moisture-dependent differences. While machine learning classification proved feasible, limitations include VOC variability, wounding interference, and lack of field sensors. Future work should emphasize MOX sensor integration and cross-cultivar generalization (Barré et al., 2016).

VOC profiling provides a powerful non-visual strategy for early detection of *Fusarium circinatum* infections in pine seedlings. Using GC–MS combined with automated machine learning, the system analyzed *Pinus sylvestris*, *P. radiata*, and *P. pinea*. VOC shifts were evident by 7 dpi in *P. radiata*, delayed in *P. sylvestris*, while resistant *P. pinea* showed no significant changes, emphasizing host-specific responses. In vitro VOC analysis further distinguished *F. circinatum* from related species with high accuracy. Despite strong diagnostic potential, challenges include lack of species-specific biomarkers, variable emissions, and limited field validation. Future work should enhance VOC libraries, portability, and ML generalizability (Nordström et al., 2022).

bVOC-based biosensing offers a rapid, non-invasive method for real-time aflatoxin detection in peanuts, addressing limitations of conventional HPLC. Field trials assessed three conditions—*Aspergillus parasiticus* inoculation, *A. flavus* (Afla-Guard) biocontrol, and untreated control—through weekly bVOC sampling via Stir Bar Sorptive Extraction (SBSE) with Twisters® and 2D GC–MS (GCxGC-TOF) profiling. Machine learning ensembles (Random Forest, Extra-Trees, Gradient Boosting) enabled aflatoxin prediction, with Random Forest yielding the highest F1-score (0.80), outperforming LDA. While the system shows strong potential for food safety and precision agriculture, challenges include environmental variability, cross-contamination, and scale-up requirements. Future work should prioritize miniaturized sensors and IoT-enabled surveillance (Sabo et al., 2024).

Plant-emitted VOCs represent sustainable alternatives to synthetic agrochemicals for crop protection and yield improvement. Key classes—terpenoids, green leaf volatiles (GLVs), benzenoids, and fatty acid derivatives—regulate Systemic Acquired Resistance (SAR), Induced Systemic Resistance (ISR), hormonal signaling, and epigenetic pathways. Analytical tools such as PTR-TOF-MS, SIFT-MS, and GC–MS have demonstrated VOC efficacy against *Fusarium oxysporum*, *Botrytis cinerea*, and *Colletotrichum lindemuthianum*. Advances include CRISPR-Cas9-mediated VOC biosynthesis enhancement and nano-encapsulation for controlled release within IoT-enabled IPM frameworks. However, volatility, environmental degradation, and inconsistent delivery remain challenges. Future directions emphasize real-time monitoring, emission stabilization, and synthetic analog development for scalable precision agriculture (Truong et al., 2018).

Pythium oligandrum-derived VOCs (Po-VOCs) show strong potential as natural biostimulants and biocontrol agents for ginger (*Zingiber officinale*), particularly against rhizome rot caused by *Pythium myriotylum*. In vitro and in planta assays using *Nicotiana benthamiana* and ginger, coupled with GC–MS, identified bioactive VOCs such as 3-octanone and hexadecane that enhanced growth and resistance. Transcriptomic and metabolomic analyses revealed upregulation of auxin, cytokinin, and gibberellin pathways, correlating with higher hormone levels and reduced disease severity. While effective, challenges include VOC variability, lack of dose-response optimization, and missing field validation. Future efforts should focus on controlled-release delivery and IoT-enabled integration (Sheikh et al., 2023).

LoRa-enabled wireless sensor networks (WSNs) provide scalable, low-power solutions for real-time plant stress monitoring. A multimodal WSN deployed on *Ligustrum jonandrum* integrated CO_2, VOC, light, temperature, and humidity sensors for long-range agricultural applications. Under controlled stress conditions, reduced VOC emissions validated VOCs as reliable stress biomarkers. A recursive neural network (RNN) was further trained to predict VOC levels from environmental parameters, enhancing early stress diagnostics. While demonstrating strong potential for postharvest and transit monitoring, limitations include limited VOC resolution, sensor drift, and lack of physiological validation. Future directions emphasize sensor fusion, recalibration strategies, and large-scale field deployment (Catini et al., 2019).

MEMS-based wearable sensors offer a breakthrough in real-time, non-invasive VOC monitoring for early plant stress detection. This system integrates a nanomaterial-enhanced gas sensor, microfluidic sampling interface, and wireless transmission module to enable continuous VOC profiling under drought, pathogen, and wounding stress. In controlled experiments, the sensor showed >0.92 correlation with GC–MS, with ppb-level sensitivity and 5× faster response times, allowing rapid identification of stress-induced VOC shifts. While highly precise, challenges include sensor drift, cross-sensitivity, and the need for crop-specific calibration. Future work should explore machine learning-driven VOC recognition, sensor fusion, and large-scale deployment for climate-resilient agriculture (Li et al., 2021).

IoT-enabled sensing frameworks are advancing early disease detection in crops through nonvisual biomarkers. For Northern Leaf Blight (NLB) in maize (*Exserohilum turcicum*), a multi-sensor platform combined Bosch BME688 VOC sensors, ultrasound modules, and NPK nutrient sensors for high-frequency data acquisition. Time-series analyses using Augmented Dickey-Fuller (ADF), trend modeling, and PELT-based change point detection identified significant VOC and ultrasound shifts 4–7 days post-inoculation, preceding visible symptoms at day 14. While cost-effective and scalable, challenges include limited VOC specificity, pathogen discrimination, and lack of field validation. Future work should enhance compound selectivity, cross-varietal robustness, and large-scale deployment (Maginga et al., 2023).

IoT-integrated deep learning frameworks are transforming early maize disease detection through non-visual biomarkers. For Northern Leaf Blight (NLB), Bosch BME688 VOC sensors and OSEPP ultrasound modules were deployed across four maize varieties in Tanzanian fields, reducing detection time from 14–21 days to 4–5 days. Time-series signals underwent wavelet transformation and normalization, enabling robust learning. A hybrid CNN-LSTM model achieved an F1-score of 0.96 and

AUC of 1.00, while an LSTM-based ultrasound model reached 99.98% accuracy. Despite high precision, challenges include environmental noise, climatic variability, and model compression needs. Future directions emphasize multi-disease integration and farmer-centric IoT interfaces (Maginga et al., 2024).

Table 6: **Comparative analysis of non-visual plant disease detection techniques based on sensor type, biomarker, model, field readiness, and limitations**

Technique / Modality	Sensor Type	Biomarker Targeted	Model / Analysis Used	Field Readiness	Key Limitation
Non-Destructive Vis/NIR Sensing (Wang et al., 2022)	Vis/NIR Spectroscopy	Soluble Solids, pH, Firmness	MLR, PLS, BPNN	Medium	Spectral overlap; low accuracy in pH/FM
Fluorescent Array Fungal Detection (Santonocito et al., 2023)	Organic Fluorophore Sensor	Fungal VOCs	PLS-DA	Medium	Lower sensitivity than qPCR
Hybrid Physiological Stress Sensor (Hossain & Tabassum, 2023)	Multi-modal SA/ET/VPD/strain	Hormonal + Physical Stress	Pearson Correlation	Medium	Sensor degradation; recalibration needs
Biomimetic Stem Growth Wearable (Zhang et al., 2022)	Laser-Induced Graphene	Stem Diameter Micro-strain	Signal Analysis	High	Wi-Fi dependency; no prediction model
Real-Time Citrus VOC Biosensing (Chalupowicz et al., 2020)	Bioluminescent E. coli + GC-MS	VOC–Toxicity Indicators	Signal Pattern Matching	Medium	Cross-reactivity; calibration complexity
Grape Botrytis VOC Profiling (Barré et al., 2016)	SPME + GC-MS	GLVs, Early Fungal VOCs	PLS-DA	Low–Medium	Postharvest variability; not real-time
Pine Fusarium VOC Detection (Nordström et al., 2022)	GC-MS	Fungal VOC Signatures	ML Classifiers	Low	Species-specific variability
Aflatoxin Detection in Peanuts (Sabo et al., 2024)	Twister SBSE + GC-MS	Aflatoxin VOCs	Random Forest, GBC	Medium	Cross-contamination; field variability
Sustainable Crop Protection via VOCs (Truong et al., 2018)	PTR-MS, SIFT-MS, GC-MS	Defensive VOC Classes	Narrative/Review	Low	Volatility, encapsulation challenges
Pythium VOCs in Ginger Defense (Sheikh et al., 2023)	GC-MS	3-Octanone, Hexadecane	Transcriptomics, Disease Index	Medium	Dose-response not defined
LoRa-based VOC WSN (Catini et al., 2019)	LoRa VOC/Env Sensors	Stress VOC Patterns	Recursive Neural Network	Medium	Coarse VOC signal; validation needed
Wearable MEMS VOC Sensor (Li et al., 2021)	MEMS, Nanomaterials	Stress-Induced VOCs	Signal correlation	High	Sensor drift, cross-sensitivity
IoT Detection of Maize NLB (Maginga et al., 2023)	VOC, Ultrasound, Soil NPK	Early NLB signals	ADF, PELT Trend Analysis	Medium	No VOC compound specificity
Hybrid CNN-LSTM for NLB (Maginga et al., 2024)	VOC + Ultrasound	Stress Signatures	CNN-LSTM	Medium–High	Environmental robustness pending

As shown in the table 6 and chart 7, Non-visual disease detection systems leverage VOC profiling, biosensing, physiological sensing, and hybrid IoT frameworks to detect early plant stress before visual symptoms emerge. VOC-based GC–MS and bioluminescent biosensors offer high specificity but are constrained by lab dependency and calibration complexity. Wearable MEMS and graphene-based strain sensors enable real-time, in-field deployment with wireless transmission capabilities, though environmental drift remains a challenge. Hybrid platforms like PlantFit and CNN-LSTM demonstrate strong multimodal integration but require high computational resources. Studies utilizing LoRa and ESP32 show promise for low-cost, scalable deployment, especially in resource-limited settings. A major gap across models is the need for standardized datasets and robust validation under diverse agro-ecological conditions.

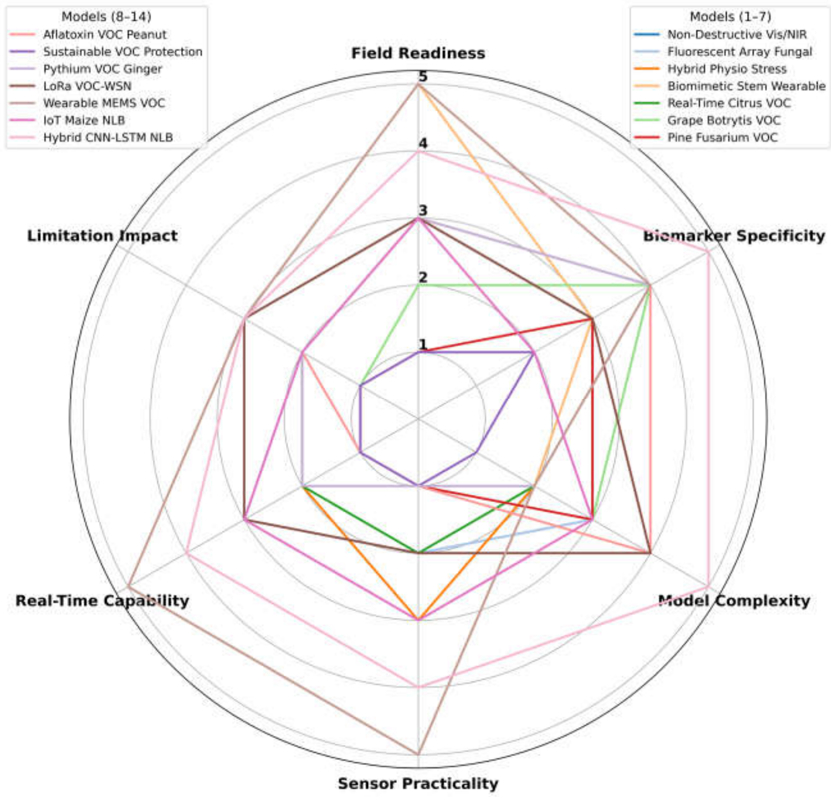

Fig 7: Radar chart showing multi-criteria comparison of non-visual plant disease detection methods

3. Critical Analysis and Proposed Framework

Early and accurate detection of plant diseases is vital for sustaining crop yield and global food security. Conventional systems rely on either visual cues (e.g., lesion classification) or non-visual biomarkers (e.g., volatile organic compounds, ultrasound, or stress sensing), each with limitations. Visual approaches, though interpretable, often detect symptoms only 7–14 days post-infection, while non-visual methods can signal stress within 3–5 days but face environmental noise and limited interpretability.

This review highlights the shortcomings of unimodal detection and proposes a Hybrid Visual–Non-Visual Framework for Early Plant Disease Detection. Though not yet empirically validated, the framework conceptually integrates image-based deep learning for spatial symptom recognition with sensor-driven analysis of physio-biochemical signals. By aligning these modalities within a unified pipeline, the system aims to improve both diagnostic accuracy and temporal responsiveness in real-world conditions. Figure 8 illustrates the proposed Adaptive Deep Learning Framework for multi-modal plant disease prediction. The proposed framework operates through five modular stages:

Multi-Modal Input Acquisition: Visual data (leaf, fruit, berry images) are captured via smartphones, UAVs, or field cameras, while non-visual inputs (VOC emissions, stem microstrain, soil parameters, ultrasound signals) are collected using MEMS sensors, wearables, or IoT nodes.

Pre-processing and Signal Conditioning: Visual inputs undergo normalization, resizing, and augmentation, whereas sensor streams are filtered, normalized, and interpolated. Temporal biomarkers such as VOC fluctuations are encoded with sliding windows for downstream analysis.

Feature Extraction: The visual branch employs lightweight CNNs (e.g., ALAD-YOLO, MA-Net, MobileNet-GRU) for spatial lesion identification (Rizwan et al., 2024). The sensor branch leverages

1D-CNNs for local signal features, while GRU/LSTM models capture stress progression dynamics (Li et al., 2019; Qin et al., 2020).

Data Alignment and Fusion: A Data Alignment Module synchronizes asynchronous streams by time or sampling rate. Fusion is supported at three levels: Late Fusion (decision aggregation), Feature-Level Fusion (vector concatenation), and Hybrid Fusion (Bayesian inference integrating uncertainty for biologically contextual decision-making) (Wang et al., 2024; Chaitanya & Posonia, 2024; Liu et al., 2024).

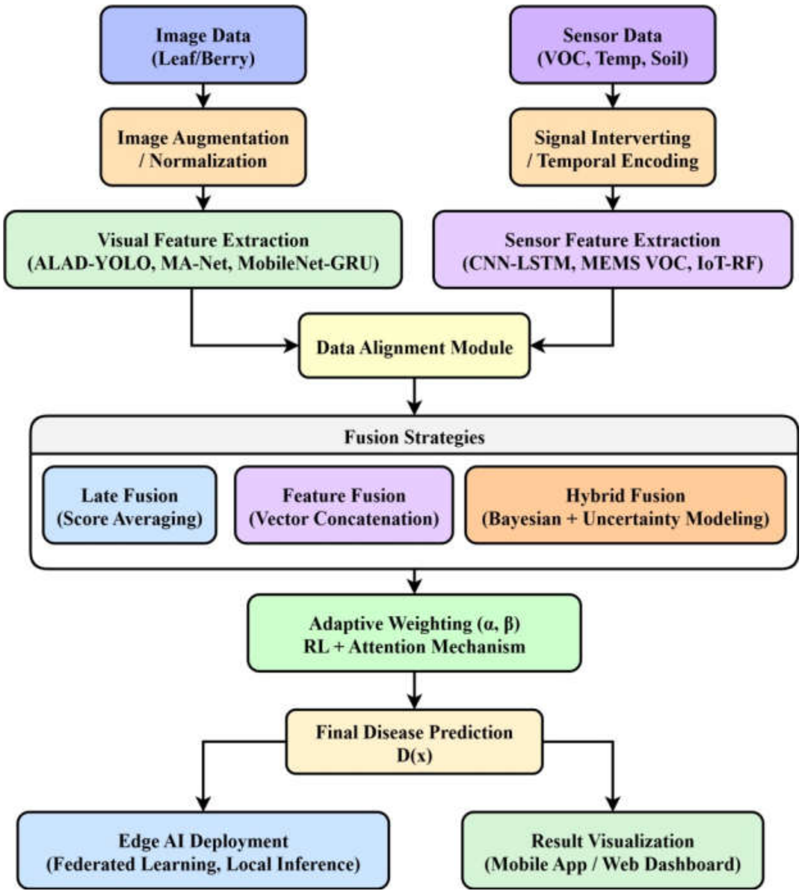

Fig 8: Proposed architecture of an Adaptive Deep Learning Framework for Multi-Modal plant disease prediction

Adaptive Decision Mechanism & Output: Predictions from visual (V) and non-visual (NV) streams are integrated via:

$$\mathbf{D(x) = \alpha V(x) + \beta NV(x)}$$

where weights α,β are optimized with reinforcement learning and attention mechanisms. Outputs include pre-symptomatic alerts, confirmed detection, or monitoring states, delivered via mobile/web dashboards with geo-tagging and intervention logs. Edge AI deployment (TensorFlow Lite, ONNX Runtime) supports on-device inference, while federated learning enables collaborative model training across farms (Joshi, 2024; Chen et al., 2024) [100, 101]. In conclusion Integrating visual and non-visual modalities enhances early disease detection, especially during asymptomatic phases, improving robustness across agro-ecological contexts. Future priorities include model generalization to diverse crops and climates, explainable AI (e.g., saliency maps, attention mechanisms), adaptive weighting optimization, and field validation of fusion strategies. These directions position the framework as a foundation for intelligent, scalable plant health monitoring in precision agriculture.

.4. Conclusion

This review provides a comprehensive synthesis of current advancements in plant disease detection, encompassing both visual and non-visual methodologies. Visual approaches, particularly deep learning-based image classification and segmentation models, have achieved significant success in identifying visible disease symptoms. However, their reliance on symptomatic features limits early-stage detection. Non-visual techniques, including volatile organic compound (VOC) sensing, microstrain monitoring, and spectral analysis, offer the potential for pre-symptomatic diagnosis, yet face challenges related to environmental variability, sensor standardization, and interpretability. By critically evaluating these complementary paradigms, this review identifies the inherent limitations of unimodal systems and presents a conceptual hybrid deep learning framework that integrates visual and non-visual data streams for robust, early, and scalable disease detection. The proposed architecture outlines a modular pipeline comprising multi-modal data acquisition, feature extraction, signal fusion, and adaptive decision-making—laying a theoretical foundation for future research and development. Advancing this vision will require coordinated efforts across multiple domains. Key priorities include the creation of benchmark multi-modal datasets, optimization of fusion and weighting strategies, deployment of lightweight models on edge devices, and the integration of explainable AI tools to improve user trust and adoption. Furthermore, ensuring model generalization across diverse crops, pathogens, and agro-climatic zones remains essential for practical viability. Overall, this work contributes not only a state-of-the-art review of plant disease detection technologies but also proposes a forward-looking research agenda that can drive the development of next-generation, intelligent, and field-ready diagnostic systems in precision agriculture.

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