



Integrated Non-Invasive Sensing and Artificial Intelligence for Real-Time Plant Stress Diagnosis in Precision Agriculture

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Abstract: Global agriculture is confronting escalating challenges from both biotic and abiotic stressors, necessitating the development of rapid, accurate, and non-invasive diagnostic tools for sustainable crop management. Traditional visual inspection and chemical treatment approaches are reactive, labor-intensive, and limited in scalability. This paper presents a comprehensive review and synthesis of state-of-the-art non-invasive sensing technologies integrated with Artificial Intelligence (AI) for real-time plant stress diagnosis in Precision Agriculture (PA). Two complementary modalities are critically examined: Visible-Spectrum Imaging coupled with Deep Learning (DL) and Thermal Infrared (TIR) Sensing.

Visible-spectrum imaging, powered by advanced Convolutional Neural Network (CNN) architectures—including hybrid and optimized models—has achieved near-perfect accuracy ($\approx 99\%$) in controlled conditions for classifying tomato leaf diseases such as early blight and Septoria leaf spot. However, the review highlights a severe generalization gap, where model accuracy drops drastically (to $\sim 71\%$) in real-world scenarios due to domain shifts in lighting, background, and image variability. To address interpretability and trust, Explainable AI (XAI) methods like Gradient-weighted Class Activation Mapping (Grad-CAM) are increasingly incorporated, while model quantization enables lightweight, real-time deployment on edge devices.

Complementarily, TIR sensing enables early physiological stress detection through parameters such as leaf temperature and Crop Water Stress Index (CWSI), which quantitatively estimate water deficit and stomatal conductance changes. Low-cost thermal imaging systems integrating sensors like MLX90640 and DHT22 have made continuous monitoring feasible for controlled environments. Yet, TIR's diagnostic power is constrained by environmental dependency and signal unspecificity, as thermal variations may result from multiple stress factors.

The paper proposes a multimodal data fusion framework that unites TIR's early stress alerts with DL's disease-specific classification to overcome the individual limitations of each system. This integrated pipeline—combining early functional monitoring with precise symptomatic diagnosis—presents a scalable path toward autonomous, real-time crop health management. Future research directions include enhancing DL robustness via heterogeneous datasets, standardizing TIR data interpretation, and embedding XAI-driven transparency within edge-deployable systems. The convergence of AI and non-invasive sensing thus represents a transformative step toward intelligent, resilient, and sustainable agriculture.

Keywords: Precision Agriculture, Deep Learning, Thermal Infrared Sensing, Plant Stress Diagnosis, Explainable AI, Crop Water Stress Index, Multimodal Data Fusion.

I. INTRODUCTION

1.1. Context and Global Agricultural Challenge

Global food production faces immense pressure from a growing population, exacerbated by the increasing frequency and intensity of environmental and biotic stressors. Plant diseases alone account for estimated crop losses of 10% to 30% globally, with major staple and commercial crops, such as tomatoes, being particularly vulnerable to a wide array of pathogens (fungi, bacteria, and viruses). The traditional methods of disease management—relying on manual visual inspection and subsequent chemical treatments—are often reactive, non-scalable, labor-intensive, and prone to subjective human error. These limitations necessitate the urgent adoption of Precision Agriculture (PA) technologies [Cengil & Çınar, 2021].



1.2. The Emergence of Non-Invasive Diagnostic Systems

Precision Agriculture's success is fundamentally dependent on rapid, accurate, and non-invasive diagnostic capabilities. This review focuses on the state-of-the-art advancements in two crucial non-invasive modalities that leverage Artificial Intelligence (AI) to automate plant health monitoring:

Visible-Spectrum Imaging and Deep Learning (DL): This approach focuses on the morphological and color changes (symptoms) that manifest late in the disease cycle, offering high specificity in disease classification.

Model Interpretability

To build trust and allow for expert validation of an AI-driven diagnosis, recent studies have incorporated explainable artificial intelligence (XAI) techniques. A key method is Gradient-weighted Class Activation Mapping (Grad-CAM), which visually highlights the specific regions of the input image that the model uses to make its classification decision. This approach helps confirm that the network is focusing on actual disease symptoms (like lesions) rather than irrelevant image features (like background or lighting), enhancing the reliability of classification for diseases such as Septoria leaf spot.

Gradient-weighted Class Activation Mapping (Grad-CAM) is used to enhance the reliability of a deep learning model's classification by visually highlighting the regions of the input image that are most important for the prediction. In a successful classification, the Grad-CAM heat map (often red/yellow) should be tightly localized over the visible disease symptoms, such as the distinct lesions characteristic of Septoria leaf spot.



Fig. 1 Sample Grad-CAM Visualization for Septoria Leaf Spot in Tomato Leaf Classification

2. Thermal Infrared (TIR) Sensing: This technique measures physiological changes (transpiration, temperature) that can occur early, acting as a functional indicator of plant stress, often before visible symptoms appear [Pineda et al., 2021].

This paper critically reviews the architectures, performance, deployment challenges, and synthesis opportunities presented by these two modalities, ultimately outlining a roadmap for future research in integrated diagnostic systems.

2. DEEP LEARNING AND VISIBLE-SPECTRUM IMAGING FOR BIOTIC STRESS CLASSIFICATION

Deep Learning, particularly the application of Convolutional Neural Networks (CNNs), has revolutionized the classification of plant diseases based on symptomatic leaf images.

2.1. Advanced CNN Architectures and Performance Benchmarks

Initial efforts in agricultural DL focused on standard CNNs, but recent studies have achieved high performance through architectural innovation and optimization.

2.1.1. Architectural Innovation

- **Hybrid CNN Models:** Recognizing the robust feature extraction capabilities of established architectures, researchers developed Hybrid CNN models that combine features extracted from multiple pre-trained networks, such as AlexNet, ResNet50, and VGG16. By employing feature selection techniques like Minimum Redundancy Maximum Relevance (mRMR), these fused features are fed into traditional classifiers, achieving



superior performance in classifying bacterial, viral, and fungal diseases simultaneously [Cengil & Çınar, 2021].

- Enhanced and Optimized CNNs: Other studies focused on internal network optimization, proposing Enhanced Convolutional Neural Networks (ECNN) tailored to identify specific diseases such as Late Blight and Bacterial Canker [Saranya et al., 2020].
- Performance Metrics: On clean, controlled datasets (like the PlantVillage dataset), these models have achieved remarkable accuracy. One state-of-the-art system, comparing multiple recent DL models across nine different tomato diseases, reported an average classification accuracy of 99.12% [Afify et al., 2024].

2.2. The Critical Challenge of Robustness and Generalization

Despite the high performance demonstrated in controlled laboratory environments, the central challenge for DL models is robustness and generalization to real-world deployment. The results reported in [Afify et al., 2024] serve as a crucial benchmark for this issue: the highly accurate model (99.12% on its test set) suffered a catastrophic drop in performance to 71.43% when tested on entirely new, unseen images downloaded from the Internet. This generalization gap is attributed to significant domain shift caused by real-world variability in lighting, background clutter, occlusions, and image quality. Bridging this gap requires:

1. Training on heterogeneous, large-scale, and non-curated datasets.
2. Implementing robust data augmentation and domain adaptation techniques.

2.3. Interpretability (XAI) and Edge Deployment

For AI systems to be adopted by farmers and trusted by agricultural regulators, the "black box" nature of deep learning must be mitigated.

- Explainable AI (XAI): Research has begun integrating XAI techniques, such as Gradient-weighted Class Activation Mapping (Grad-CAM), into diagnostic pipelines [Berdin & Caduyac, 2025]. Grad-CAM works by producing a coarse localization map that highlights the regions of the input image that are most important for the model's final classification decision.



Fig 2: Left to right: early blight, Septoria leaf spot, healthy leaves of the testing set.

Grad-CAM visualization applied to a ResNet-50 model, demonstrating the specific regions of the tomato leaf image that the network focuses on to classify the disease. This technique is vital for verifying model reliability and transparency.

- Edge AI and Quantization: For real-time, on-site diagnostics via smartphones or field robotics, models must be small and fast. This is achieved through techniques like model quantization, which reduces the bit-precision of the model's weights (e.g., from 32-bit to 16-bit floating point). This process can reduce the model size by approximately 50% and significantly decrease inference time with only a minimal trade-off in accuracy (e.g., from 91.22% to 90.10% for a ResNet-50 model) [Berdin & Caduyac, 2025].



TABLE I COMPARISON OF RESNET-50 MODEL PERFORMANCE FOR TOMATO LEAF DISEASE CLASSIFICATION

Class	Grad-CAM labels										
	A	B	C	D	E	F	G	H	I	J	K
Early blight	0	0	0	0	1	3	0	10	16	123	1
Septoria	0	0	0	0	0	1	0	1	4	37	2
Healthy	0	0	1	4	3	9	0	19	25	82	0
Total	0	0	1	4	4	13	0	30	45	242	3

3. THERMAL INFRARED SENSING FOR PHYSIOLOGICAL STRESS MONITORING

Thermal infrared (TIR) imaging provides a functional approach to diagnostics by monitoring the plant's physiological status, often preceding the manifestation of visible symptoms.

Recent efforts have focused on developing cost-effective and scalable thermal imaging systems, particularly for indoor farming. These systems integrate affordable thermal sensors with environmental monitoring to calculate key stress indices. The Crop Water Stress Index (CWSI), which is calculated from thermal data and ranges from 0 (optimal) to 1 (deficiency), is a primary metric for quantifying plant water relations and vascular function

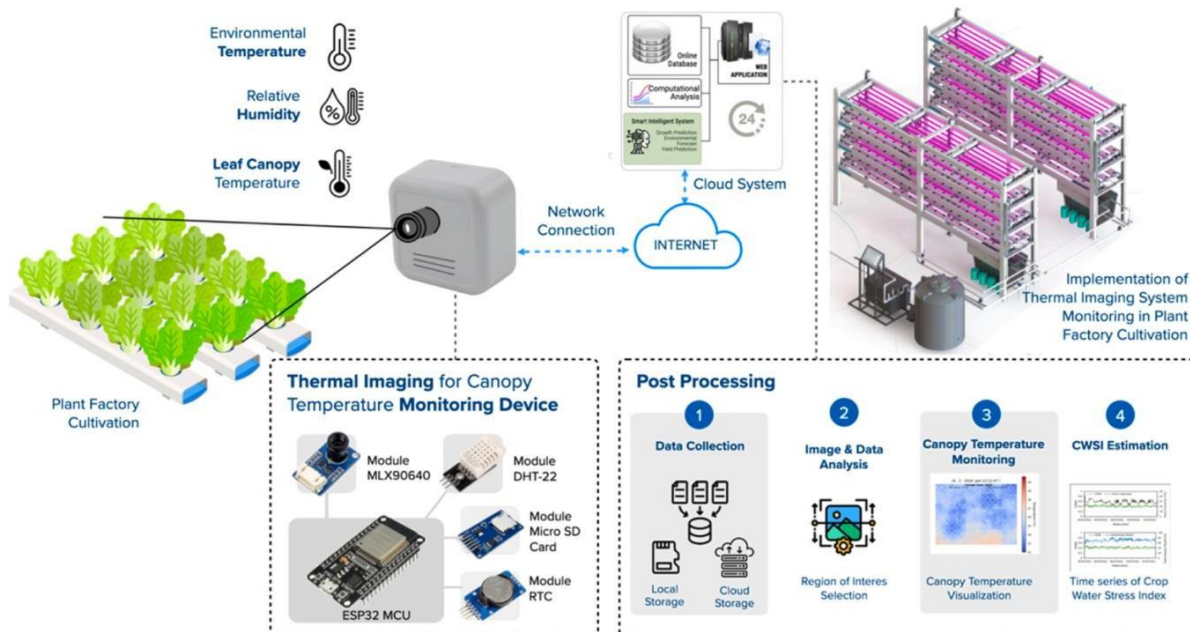


Fig 3: System Architecture of a Low-Cost Thermal Imaging System

3.1. Theoretical Basis of Thermal Stress Detection

- The Leaf Temperature Indicator: Leaf temperature, measured via TIR in the 8–14 μm wavelength range, is a critical, non-invasive indicator of plant health [Pineda et al., 2021]. The temperature is principally controlled by transpiration (evaporative cooling), which is, in turn, regulated by stomatal aperture.
- Physiological Response to Stress: When a plant experiences stress—whether due to abiotic factors (e.g., water deficit, salinity) or biotic factors (e.g., pathogen invasion)—it triggers a defensive mechanism of stomatal closure. This closure reduces transpiration, inhibits evaporative cooling, and results in a measurable increase in leaf surface temperature. TIR sensing is an essential tool in plant phenotyping due to this direct link between temperature and function [Pineda et al., 2021].



3.2. Low-Cost Systems and Quantitative Abiotic Assessment

Recent advancements have focused on making TIR technology accessible for widespread agricultural use, moving beyond high-cost research-grade cameras.

- **Low-Cost Hardware:** Studies have successfully developed low-cost thermal imaging systems utilizing affordable microbolometer arrays (e.g., MLX90640) integrated with environmental sensors (e.g., DHT22) [Nugroho et al., 2025]. These systems are particularly valuable for continuous monitoring in Controlled Environment Agriculture (CEA).
- **Crop Water Stress Index (CWSI):** The primary quantitative application of agricultural TIR is the calculation of the Crop Water Stress Index (CWSI). CWSI is a normalized, unitless metric (ranging from 0 to 1) that estimates the degree of water deficit by comparing the difference between the plant's temperature and the ambient temperature relative to the maximum theoretical difference under non-transpiring conditions.

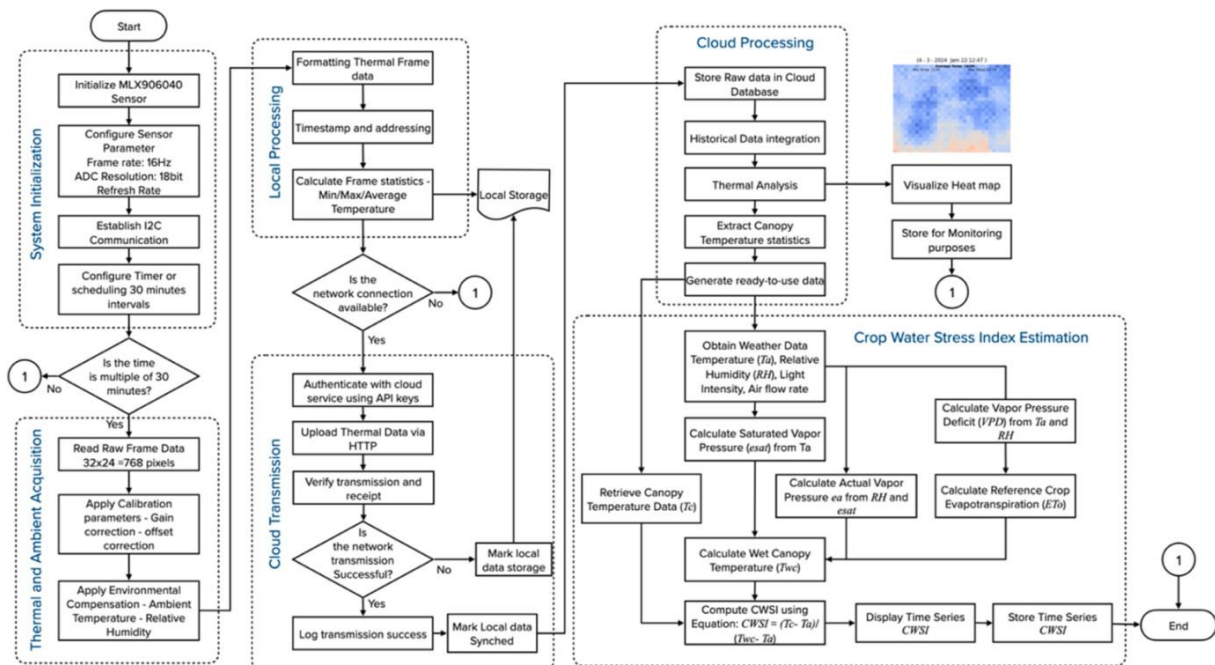


Fig 4 : Flow chart of the mechanism of data acquisition, process of the thermal imaging system device to cloud system, and crop water stress index estimation.

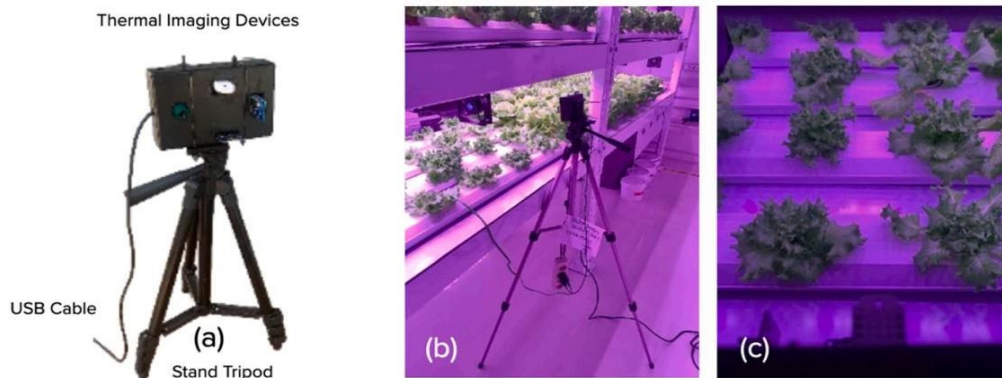


Fig 5 : Thermal camera system implementation scheme: (a) Thermal imaging system setup; (b) Thermal camera system implementation; (c) Point of view of the thermal camera system.



The architecture of a low-cost thermal imaging system, demonstrating the integration of the thermal camera and environmental sensors required to continuously monitor leaf temperature and calculate the Crop Water Stress Index (CWSI), a quantitative measure of water stress.

The Crop Water Stress Index (CWSI) is a mathematical model derived index that utilizes canopy temperature and ambient temperature as parameters. Canopy temperature exhibits an inverse relationship with leaf stomatal conductance and transpiration rate. In response to water stress, plants initiate a self-preservation mechanism by closing their stomata, resulting in a reduction in transpiration rate and a subsequent increase in canopy temperature. This stomatal closure serves as an initial response to drought stress, functioning as a protective measure to prevent excessive water loss through transpiration. As temperature rises, to further conserve water and maintain plant health. This change in canopy temperature serves as an indicator of water stress.

The values range from 0 to 1, with values closer to 0 indicating lower water stress and optimal conditions for plant growth and development. Conversely, values approaching 1 signify severe water stress, resulting in hindered plant growth due to water deficiency. The threshold CWSI values vary among different crop species, reported that the CWSI threshold range for winter wheat is between 0.26 and 0.38 to avoid adverse effects of water shortage. A CWSI value of 0.0–0.3 generally indicates that crops are well-watered, while a value of 0.3–0.6 suggests water stress (Qin et al., 2021). Research on CWSI values for lettuce has been conducted by who determined baseline temperatures for calculating the Crop Water Stress Index (CWSI) in greenhouse-cultivated lettuce crops. The calculation of the Crop Water Stress Index (CWSI) involves employing algorithms that consider the relationship between canopy temperature, ambient temperature, and relative humidity. Specifically, the Penman-Monteith model, which accounts for heat transfer through evaporation, radiation, and convection, is commonly used as a basis for CWSI calculations. The algorithm utilizes the recorded data of average canopy temperature T_c , ambient temperature T_a , and vapor pressure deficit (VPD) – derived from ambient temperature and relative humidity measurements – to estimate the reference crop evapotranspiration ET_0 . The CWSI is then computed using the following

$$\text{Eq. (1): } \text{CWSI} = (T_c - T_a) / (T_{\text{ref}} - T_a) \quad \dots\dots(1)$$

where T_{ref} represents the canopy temperature of a well-watered reference crop, typically assumed to be the wet canopy temperature T_{wc} , calculated using (2):

$$\text{Eq. (1): } T_{wc} = T_a + \Delta(e_{\text{sat}} - e_a) (T_{\text{max}} - T_a) / \Delta(e_{\text{sat,ref}} - e_{a,\text{ref}}) \quad \dots\dots(2)$$

Where $e_{\text{sat,ref}} - e_{a,\text{ref}}$ Here, e_{sat} and e_a denote the saturated and actual vapor pressure, respectively, and the Δ symbol represents the slope of the curve relating vapor pressure deficit to canopy temperature.

This calculation takes into account the physiological response of the crop to water stress, with the CWSI values typically ranging from 0 (no stress) to 1 (severe stress). CWSI values are classified into well-watered (0.0–0.3), moderate stress (0.3–0.6), and severe stress (>0.6) categories, with results mapped across the indoor growing area and stored for time series analysis.

TABLE 2: CROP WATER STRESS INDEX (CWSI) RANGE AND INTERPRETATION

CWSI Range	Stomatal Conductance	Plant Water Status Interpretation
0.0 - Low	High (Open)	Optimal Plant Growth / No Water Stress
High - 1.0	Low (Closed)	Significant Water Deficiency / High Vascular Stress

3.3. Challenges: Environmental Dependency and Unspecificity

Despite achieving high performance in controlled, lab-like environments (e.g., an average accuracy of 99.12% on a standardized test set), a central challenge remains the significant drop in model accuracy when applying the deep learning system to new, unseen field data that better reflects real-world variability. This phenomenon, known as the generalization gap, was evidenced by a study where a high-performing model's accuracy immediately dropped to 71.43% when tested on new images scraped from the internet [Afify et al., 2024]. To mitigate this, future efforts must focus on advanced techniques like dataset enrichment (incorporating a wider range of lighting, backgrounds, and disease stages) and regularization methods such as label smoothing to maximize the system's robustness and generalization ability in complex agricultural settings.

Despite its utility, TIR sensing faces critical limitations:



1. Environmental Dependency: Accurate leaf temperature reading is extremely sensitive to ambient conditions. The interpretation of thermal data requires complex corrections factoring in wind speed, solar radiation, air temperature, and humidity, as these factors drastically influence the temperature gradient between the leaf and the air [Pineda et al., 2021].
2. Lack of Specificity: The thermal signal is an unspecific indicator of stress. A temperature rise signifies that the stomata are closed, but this closure is an immediate defensive response to multiple stimuli (drought, salinity, fungal infection, pest damage). Therefore, TIR data alone cannot provide a specific diagnosis required for targeted disease management.

4. SYNTHESIS, RESEARCH GAPS, AND FUTURE DIRECTIONS

The reviewed studies establish that both visible-spectrum DL and TIR sensing are individually robust technologies, but their limitations—the generalization gap for DL and the unspecificity for TIR—require an integrated solution.

4.1. The Imperative for Multimodal Data Fusion

The most critical research direction is the development of multimodal diagnostic systems that synergistically combine thermal and visible data.

- The Diagnostic Pipeline: A fused system could operate on a two-stage pipeline:
 1. Early Alert (TIR): A low-cost TIR sensor provides a continuous, early warning signal of physiological stress (increased CWSI or leaf temperature).
 2. Specific Diagnosis (DL): This early alert triggers a focused acquisition of high-resolution visible-spectrum images, which are then analyzed by a quantized, interpretable DL model to provide a specific classification (e.g., "Early Blight").
- Benefits: This integration combines the timeliness of functional monitoring with the specificity of symptomatic classification, creating a far more robust and actionable diagnostic tool.

4.2. Research Gaps and Standardization

Future research must prioritize closing the critical gaps identified in the current literature:

4.2.1. Addressing the Generalization Gap in DL

The significant drop in accuracy on unseen data (Table 1) mandates a shift in dataset philosophy. Researchers must move away from controlled, monochromatic-background datasets toward creating and utilizing vast, open-access, heterogeneous datasets that accurately reflect the noise, clutter, and variability of real-world field conditions. Techniques for domain randomization and simulated sensor data are necessary to train models robust enough for universal deployment.

4.2.2. Advancing Explainable and Deployable AI

The adoption of XAI tools like Grad-CAM must become standard practice, not just a proof-of-concept. Furthermore, research must continue to optimize quantization and pruning methods to ensure that complex, multi-modal DL models can be seamlessly executed on resource-constrained edge devices (UAVs, mobile phones, field robots) to facilitate real-time inference.

4.2.3. Standardization in TIR Data Protocol

The interpretation of thermal data remains highly dependent on non-standardized environmental corrections. Future work must establish universal protocols and calibration standards for CWSI calculation and temperature measurement across different climatic zones and sensor types to ensure that TIR data is reliably comparable and actionable globally.

5. CONCLUSION

The confluence of non-invasive sensing and artificial intelligence marks a definitive paradigm shift in plant pathology. Deep Learning with visible-spectrum imaging has achieved high accuracy in symptomatic disease classification, though its utility is currently hindered by a significant generalization gap. Thermal Infrared sensing offers a pathway to early, functional stress detection and quantitative abiotic monitoring, but is inherently limited by the unspecificity of its signal. The roadmap for next-generation agricultural diagnostics requires embracing multimodal data fusion, leveraging the strengths of both modalities. By



focusing on creating robust, interpretable, and quantized AI systems trained on diverse, real-world data, the vision of autonomous, real-time crop health management in Precision Agriculture can be fully realized.

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