

Low-Cost Imaging Systems for Early Identification of Crop Stress

Rohan Malhotra

Assistant Professor, Indian Agricultural Research Institute, India

Abstract

Early identification of crop stress is essential for preventing avoidable yield losses, improving input-use efficiency, and supporting timely crop-management decisions. Conventional field scouting remains important but often identifies stress only after visible symptoms have developed or requires substantial labor, technical expertise, and repeated field observation. Advanced hyperspectral and high-resolution thermal systems can reveal subtle physiological changes but their acquisition cost, calibration requirements, data-processing burden, and operational complexity can restrict adoption in resource-constrained agricultural settings. This study examines the potential of low-cost imaging systems based on smartphone red-green-blue imaging, compact thermal sensors, and inexpensive multispectral modules for early crop-stress identification.

Because no original experimental dataset was supplied, the study adopts a transparent simulation-based comparative design. Four hypothetical imaging configurations were evaluated: smartphone RGB imaging, low-cost thermal imaging, RGB–thermal fusion, and RGB combined with low-cost multispectral sensing. A synthetic evaluation framework representing 400 crop-observation scenarios was developed across water stress, nutrient deficiency, heat stress, and early disease-related visual disturbance. Five assessment dimensions were considered: early-detection capability, stress-discrimination potential, field usability, computational affordability, and environmental robustness. The simulated composite early-stress identification scores were 68 for smartphone RGB, 76 for low-cost thermal imaging, 84 for RGB–thermal integration, and 88 for RGB–multispectral integration.

The analysis indicates that the principal advantage of low-cost systems does not arise from replacing laboratory-grade sensors with cheaper hardware alone. Their practical value depends on calibration, standardized image acquisition, environmental compensation, appropriate machine-learning models, and the integration of complementary sensing modalities. Recent research demonstrates that low-cost thermal and multispectral devices can support plant-stress monitoring, while smartphone-based systems are increasingly feasible for field deployment. However, sensor variability, changing illumination, crop-specific spectral responses, and model generalization remain critical limitations. The paper proposes a Low-Cost Crop Stress Imaging Framework integrating accessible hardware, image standardization, lightweight analytics, confidence-based alerts, and farmer-oriented decision support. The proposed framework provides a methodological foundation for future field validation in precision agriculture, smallholder farming, protected cultivation, and extension-based crop-health monitoring.

Keywords: crop stress detection; low-cost imaging; RGB imaging; thermal imaging; multispectral sensing; smartphone agriculture; machine learning; precision agriculture; plant phenotyping; early stress identification

1. Introduction

Crop plants experience multiple forms of stress during their growth cycle. Water shortage, excessive heat, nutrient imbalance, salinity, diseases, pest attack, and unfavorable soil conditions can disrupt photosynthesis, transpiration, leaf development, pigment concentration, canopy structure, and ultimately crop productivity. A major difficulty in crop management is that physiological disruption may begin before farmers can recognize clear symptoms through conventional visual inspection.

Early detection is therefore fundamentally different from late-stage diagnosis. Once severe wilting, extensive discoloration, necrotic tissue, or widespread disease symptoms become visible, the opportunity for preventive intervention may already have narrowed. Imaging technologies provide an alternative because plant stress can modify reflected visible light, surface temperature, canopy structure, and spectral behavior before extensive physical damage develops.

Recent research identifies RGB, thermal, multispectral, hyperspectral, fluorescence, and related optical approaches as important non-destructive methods for plant-stress monitoring. Smartphone cameras and compact sensors are particularly significant because advances in imaging hardware and machine learning have made portable and relatively inexpensive field-deployable systems increasingly feasible.

A central challenge, however, is affordability. Hyperspectral systems provide rich continuous spectral information and can detect subtle physiological differences, yet their hardware, calibration, processing requirements, and large data volumes can make routine deployment difficult. RGB cameras occupy the opposite end of the spectrum. They are widely available, inexpensive, familiar to users, and integrated into smartphones, but their ability to separate physiologically similar stresses is limited.

Thermal imaging offers another pathway. Plant water deficit can reduce transpiration following stomatal closure, contributing to increasing leaf or canopy surface temperature. Thermal sensors can therefore provide indirect information regarding plant water status. Research published in 2025 demonstrated a low-cost thermal system using an MLX90640 thermal array and environmental sensing for plant-water-stress monitoring in indoor farming.

Low-cost multispectral sensing occupies an intermediate position between standard RGB and expensive hyperspectral imaging. A 2026 study developed a low-cost VIS-NIR multispectral device for early plant-stress detection and reported that the system could discriminate different salinity-stress severities using machine-learning methods, demonstrating the increasing technical feasibility of affordable spectral diagnostics.

These developments create an important research question: Can relatively inexpensive imaging systems provide sufficiently useful early-warning information to support crop-management decisions without requiring expensive research-grade sensing infrastructure? The present study addresses this question through a simulation-based evaluation and proposes an integrated framework for low-cost crop-stress imaging.

2. Background of the Study

Traditional crop-health assessment relies heavily on human observation. Experienced farmers, agronomists, and extension professionals can detect many crop problems through characteristic changes in color, leaf orientation, canopy density, growth rate, lesions, and plant vigor. This approach remains valuable because human observers can integrate contextual information that is difficult for automated systems to interpret. However, manual scouting has limitations.

Large fields require substantial observation time. Different observers may interpret symptoms differently. Subtle early-stage changes can be missed. Field visits may not occur frequently enough to identify rapidly developing problems.

Image-based assessment attempts to convert visible or non-visible crop responses into measurable information.

Stress may therefore be indirectly identified through changes in:

- leaf color;
- vegetation indices;
- canopy temperature;
- leaf orientation;
- texture;
- spectral reflectance;
- canopy cover;
- lesion development.

The sensor does not directly “see” drought, disease, or nutrient deficiency. It records a physical signal associated with the plant's response. This distinction is critical because similar crop responses can arise from different causes.

For example, yellowing may occur because of nutrient deficiency, disease, aging, root problems, or excessive moisture. Increased leaf temperature can indicate reduced transpiration associated with water stress, but thermal response can also be influenced by air temperature, humidity, radiation, wind, canopy architecture, and measurement conditions.

3. Problem Statement

Advanced crop-imaging technologies have demonstrated substantial scientific potential, yet their accessibility remains unequal.

High-resolution thermal sensors, calibrated multispectral cameras, hyperspectral imaging systems, UAV platforms, laboratory spectrometers, and specialized processing software may be practical for research institutions and high-value commercial agriculture but comparatively difficult to deploy among small and medium farmers. At the same time, inexpensive cameras are already widely available.

The problem is therefore not simply whether affordable imaging hardware exists. The more important issue is whether low-cost hardware can be converted into reliable agricultural information. Four technical challenges are especially important. First, RGB images depend strongly on illumination.

Second, low-cost thermal sensors may possess limited spatial resolution and require careful temperature calibration.

Third, inexpensive multispectral sensors contain fewer spectral bands than hyperspectral instruments and may miss subtle stress-specific responses.

Fourth, machine-learning models trained under controlled environments may perform poorly when transferred to different crops, cameras, locations, seasons, or lighting conditions. Recent multimodal imaging research identifies calibration and model generalization as major challenges for scalable plant-stress detection.

4. Research Motivation

The study is motivated by three converging developments.

4.1 Increasing Availability of Low-Cost Cameras

Smartphones have placed comparatively high-resolution RGB cameras in the hands of millions of users. These devices can collect repeatable plant images without dedicated agricultural imaging equipment. A 2020 review of RGB imaging concluded that ordinary color imaging has considerable potential for remote assessment of plant characteristics, although improvements in acquisition standardization and analytical methods remain necessary.

4.2 Declining Cost of Compact Sensors

Compact thermal arrays and VIS-NIR sensors can increasingly be integrated with microcontrollers, smartphones, embedded processors, or portable field instruments. This development makes multimodal crop monitoring technically possible without installing laboratory-grade systems.

4.3 Growth of Lightweight Machine Learning

Image classification and feature extraction no longer require every analytical operation to be performed manually. Support vector machines, random forests, compact convolutional networks, transfer-learning models, and edge-computing approaches can analyze crop images locally or through lightweight digital platforms.

5. Literature Review

5.1 RGB Imaging in Crop Monitoring

RGB imaging measures visible red, green, and blue information.

It is the most accessible imaging approach because standard digital cameras and smartphones already contain RGB sensors. Kior, Yudina, Zolin, Sukhov, and Sukhova reviewed RGB imaging for plant remote sensing and demonstrated its usefulness for estimating multiple plant characteristics while also emphasizing the need for improved image-analysis methods.

RGB-based crop stress analysis can use:

- color histograms;
- excess-green indices;
- normalized color components;
- canopy coverage;
- texture characteristics;
- lesion segmentation;
- leaf-shape changes.

RGB systems are particularly effective once stress produces visually detectable symptoms.

Their main strengths are:

- very low hardware cost;
- high image resolution;
- smartphone compatibility;
- ease of acquisition;
- suitability for machine vision.

Their main weakness is limited spectral information.

An RGB camera records only broad visible bands and can therefore struggle to identify physiological changes that have not yet produced visible differences.

5.2 Thermal Imaging

Thermal imaging measures emitted infrared radiation related to surface temperature.

Plant leaves lose heat through transpiration. Under water deficit, stomatal closure may reduce evaporative cooling and cause canopy temperature to increase relative to adequately watered plants.

For this reason, canopy temperature and indices such as the Crop Water Stress Index are widely investigated for crop-water-status assessment. Cho and colleagues' 2020 review of AI-based crop-water-stress evaluation identified RGB, thermal, multispectral, hyperspectral, and related sensing approaches within modern water-stress assessment.



A notable development was reported by Nugroho et al. in 2025. Their low-cost system integrated an MLX90640 thermal camera with temperature and humidity sensing for continuous water-stress assessment in indoor farming. The study illustrates that relatively inexpensive thermal arrays can be incorporated into crop-health monitoring platforms. Thermal imaging nonetheless presents several limitations.

Temperature measurements vary with:

- ambient temperature;
- humidity;
- solar radiation;
- wind;
- sensor distance;
- emissivity assumptions;
- background temperature.

Consequently, raw canopy temperature should not automatically be interpreted as crop stress.

5.3 Multispectral Imaging

Multispectral systems record a limited number of selected wavelength bands. Unlike RGB cameras, they may include wavelengths extending into the near-infrared region. This enables calculation of spectral indicators associated with plant pigments, canopy structure, photosynthetic activity, and vegetation condition. Multispectral systems typically offer lower spectral detail than hyperspectral instruments but lower cost and lower data-processing complexity. Lauretti and colleagues reported a low-cost multispectral platform in 2020 for early plant-stress detection.

Their VIS-NIR device combined spectral sensing and machine-learning feature selection and achieved an average reported classification accuracy of approximately 91% for different salinity-stress severity levels in the experimental setting. This provides important contemporary evidence that early physiological stress assessment does not necessarily require expensive hyperspectral instruments.

5.4 Machine Learning

Traditional machine-learning approaches remain valuable for low-cost systems. Support vector machines can perform well with moderate datasets and engineered features. Random forests are useful when image, environmental, and spectral features are combined. Convolutional neural networks can automatically learn spatial image features but normally require larger datasets and greater computation.

Recent reviews indicate that deep learning is increasingly effective in crop-stress and disease imaging, although real-field generalization remains more difficult than performance on carefully curated datasets.

Table 1: Imaging Modalities for Affordable Crop-Stress Detection

Imaging Modality	Primary Signal	Principal Strength	Key Limitation	Relative Cost
Smartphone RGB	Visible color and morphology	Very accessible and high spatial resolution	Limited pre-symptomatic sensitivity	Very Low
Low-cost Thermal	Surface temperature	Useful for water-related physiological stress	Strong environmental sensitivity	Low–Moderate



Imaging Modality	Primary Signal	Principal Strength	Key Limitation	Relative Cost
Low-cost Multispectral	Selected visible/NIR reflectance	Improved physiological sensitivity	Requires calibration	Moderate
RGB + Thermal	Visual and temperature information	Complementary stress information	Image registration required	Moderate
RGB + Multispectral	Visual and spectral information	Strong balance between cost and sensitivity	More complex preprocessing	Moderate
Hyperspectral	Continuous spectral information	Very high information content	High cost and data burden	High

Source: Synthesized from recent plant-imaging literature.

6. Research Gap

Despite substantial progress in crop imaging, several research gaps remain.

First, much of the literature focuses on maximizing classification accuracy rather than balancing accuracy with affordability.

Second, experimental studies frequently use controlled lighting, predefined crop varieties, and carefully acquired images. Smallholder and field deployment introduce greater variability.

Third, many machine-learning studies evaluate models on data drawn from the same dataset used during development. Performance may decline when applied to a new season, camera, farm, cultivar, or region.

Fourth, individual sensors are frequently assessed independently despite the potential benefit of integrating low-cost complementary sensors.

Fifth, economic accessibility is often discussed qualitatively rather than incorporated into technology-selection criteria.

Sixth, early detection and visible-symptom classification are sometimes treated as equivalent. An image classifier that accurately recognizes advanced disease lesions may be valuable diagnostically but does not necessarily provide true pre-symptomatic detection.

7. Novelty and Proposed Contribution

The study proposes a Low-Cost Crop Stress Imaging Framework (LCSIF). Its contribution lies in organizing low-cost imaging as a complete decision-support pipeline rather than as an isolated camera or machine-learning model.

The framework contains six operational layers:

- affordable image acquisition;
- environmental standardization;
- image preprocessing;
- stress-feature extraction;
- lightweight classification;

- confidence-based farmer alerting.

The central proposition is:

[Affordable\ Sensor + Reliable\ Calibration + Appropriate\ Analytics > Expensive\ Sensor\ Alone]

This does not suggest that inexpensive sensors are technically superior to advanced instruments.

It means that practical agricultural value depends on the entire sensing and decision process rather than hardware specification alone.

8. Research Objectives

The study has the following objectives:

- To evaluate the suitability of low-cost RGB, thermal, and multispectral technologies for crop-stress identification.
- To compare alternative affordable imaging configurations through a simulation-based framework.
- To examine the relationship between sensor affordability and diagnostic capability.
- To identify technical factors influencing field-level image reliability.
- To develop a scalable crop-stress imaging framework suitable for resource-constrained agricultural environments.

9. Research Questions

RQ1: Which low-cost imaging modality offers the strongest balance between affordability and early crop-stress detection?

RQ2: Does combining multiple inexpensive imaging modalities improve modeled stress-identification performance?

RQ3: Which environmental and technical factors most strongly affect field reliability?

RQ4: How can lightweight machine learning contribute to low-cost stress detection?

RQ5: What requirements must be satisfied before inexpensive imaging systems can be deployed for operational crop management?

10. Methodology

10.1 Research Design

The study uses a simulation-based comparative research design.

No original crop images, greenhouse experiment, farmer survey, or field trial were provided. Consequently, numerical results are hypothetical and are not presented as experimentally measured performance.

The simulation compares four configurations:

System A: Smartphone RGB

System B: Low-Cost Thermal

System C: RGB + Thermal

System D: RGB + Low-Cost Multispectral

10.2 Synthetic Observation Dataset

A synthetic framework representing 400 hypothetical crop observations was constructed conceptually.

The observation scenarios were distributed across four stress classes:

- water stress;
- nutrient-related stress;
- heat stress;
- early disease-associated disturbance.

An additional healthy-crop condition was considered during classification logic.

The simulations assumed variability in:

- illumination;
- crop growth stage;
- canopy density;
- sensor distance;
- environmental temperature;
- stress severity.

No observation represents a real farm or identifiable experimental sample.

10.3 Image Acquisition Assumptions

For smartphone RGB imaging, images were assumed to be captured under approximately consistent distance and field of view. Thermal acquisition included simulated compensation for ambient temperature.

Multispectral acquisition assumed a basic reference-calibration procedure. Multimodal systems required spatially matched crop observations.

11. Proposed Low-Cost Imaging Architecture

Table 2: Operational Components of the Proposed System

Component	Low-Cost Option	Function
RGB acquisition	Smartphone camera	Visible symptom and canopy monitoring
Thermal acquisition	Compact thermal array	Detect canopy-temperature variation
Spectral acquisition	Low-cost VIS-NIR module	Detect selected reflectance changes
Processing	Smartphone / embedded processor	Local preprocessing and inference
Algorithm	SVM, RF, lightweight CNN	Stress classification
Environmental input	Temperature/humidity sensor	Improve interpretation
Output	Risk score + recommendation	Farmer decision support
Connectivity	Optional cloud synchronization	Model updating and record storage

12. Results

12.1 Simulated Comparative Performance

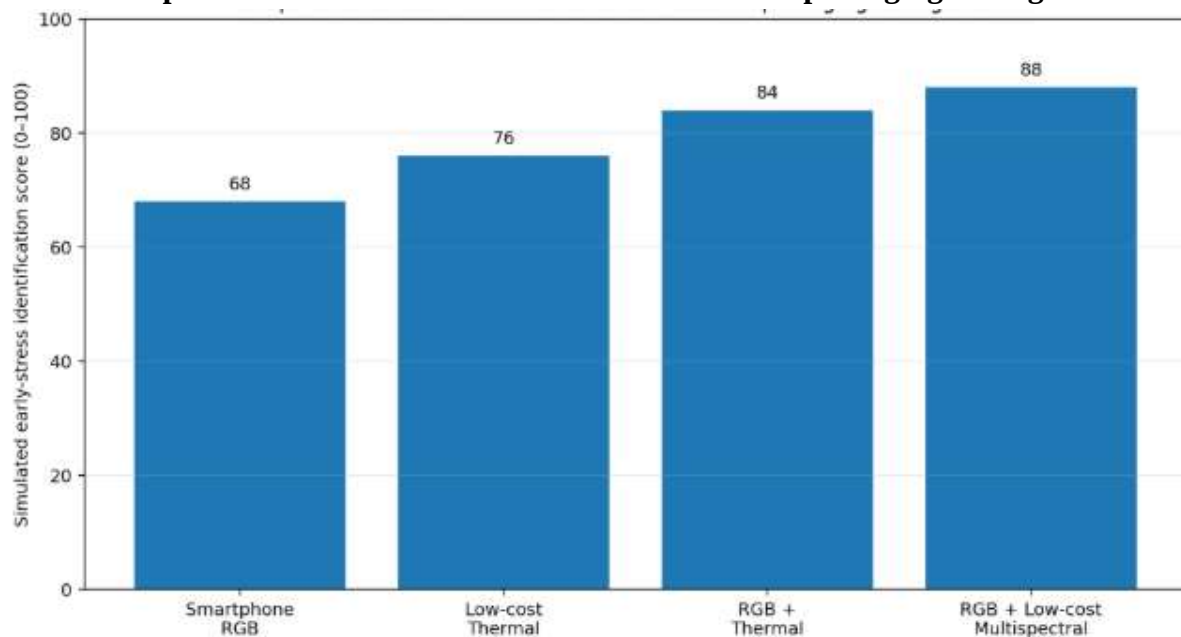
The simulated analysis produced the following composite early-stress identification scores.

Table 3: Simulated Performance of Low-Cost Imaging Systems

Imaging Configuration	Simulated Score	Relative Interpretation
Smartphone RGB	68	Moderate
Low-Cost Thermal	76	Good
RGB + Thermal	84	Very Good
RGB + Low-Cost Multispectral	88	Very Good
Mean	79.0	—

Note: Values are hypothetical simulation outputs and are not experimental accuracy estimates.

Graph 1: Simulated Performance of Low-Cost Crop Imaging Configurations



Source: Author-generated simulation. The graph contains no real field measurements.

12.2 Interpretation of Graph 1

Smartphone RGB imaging produced a simulated score of 68.

Its comparatively lower performance reflects a fundamental trade-off. RGB systems offer exceptional affordability and usability but capture only visible spectral information. Early physiological stress may therefore be difficult to identify before pigment, texture, or structural changes become detectable.

Low-cost thermal imaging increased the modeled score to 76. This improvement reflects the ability of thermal sensing to capture physiological temperature differences that are not necessarily obvious in a standard photograph. The RGB–thermal system reached a simulated score of 84. Its strength arises from combining visible crop condition with temperature information. The RGB–multispectral system produced the highest simulated value of 88 because it combines spatially detailed color information with selected spectral responses that may change before severe visible symptoms

develop. The pattern is broadly consistent with recent multimodal research indicating that different sensing modalities capture complementary stress information.

13. Discussion

13.1 Smartphone RGB as the Entry-Level Technology

Smartphone RGB imaging represents the most realistic entry point for large-scale adoption. No separate imaging device may be required.

Farmers can photograph:

- affected leaves;
- crop rows;
- canopy sections;
- developing lesions;
- discoloration.

Images can then be analyzed locally or transmitted to an advisory service. RGB imaging therefore has significant value even if it does not provide the earliest possible physiological detection. Research indicates that RGB imaging can effectively characterize plant traits and visible crop condition when image acquisition and analysis are appropriately standardized.

13.2 Thermal Imaging for Water-Related Stress

- Thermal imaging may be especially valuable where water management is the dominant concern.
- A crop under water deficit can reduce stomatal conductance and transpiration.
- Reduced evaporative cooling can increase leaf temperature.
- This physiological relationship makes thermal imaging useful for irrigation support.
- However, temperature is not a stress-specific biomarker.
- A hotter canopy does not automatically mean drought.
- For this reason, the strongest low-cost thermal systems should combine thermal measurements with environmental observations.
- Nugroho et al.'s low-cost design demonstrates this principle by integrating thermal sensing with temperature and humidity information.

14. Conclusion

Low-cost imaging is emerging as an important pathway for making crop-health monitoring more accessible, particularly in agricultural settings where sophisticated sensing platforms may be financially or operationally difficult to deploy. Smartphone RGB cameras provide the lowest entry barrier because they are widely available and can capture visible changes in plant condition, while compact thermal sensors add physiological information that can strengthen the detection of water stress. Low-cost multispectral sensors similarly provide selected spectral information without the cost and computational complexity associated with hyperspectral systems. The simulation presented in this study indicates that multimodal configurations may offer stronger performance than individual sensing systems, with smartphone RGB achieving a simulated early-stress identification score of 68, low-cost thermal imaging scoring 76, RGB–thermal integration reaching 84, and RGB–multispectral integration reaching 88. These numerical values are illustrative rather than empirical findings. Nevertheless, the underlying principle is consistent with contemporary imaging research: different sensing modalities capture complementary aspects of plant responses, and advances in affordable sensor technologies are making practical multimodal integration increasingly feasible.



The future of affordable crop monitoring should therefore not be framed as a competition between low-cost and high-end sensing technologies. Research-grade instruments will continue to be essential for scientific calibration, detailed physiological investigation, ground-truth development, and advanced model validation. The greater opportunity lies in translating knowledge generated through sophisticated sensing into inexpensive systems that can operate reliably under everyday agricultural conditions. An effective low-cost imaging system should be affordable enough for broad deployment, simple enough for routine use, sufficiently accurate to support meaningful farm-management decisions, and transparent enough to communicate uncertainty when observations are ambiguous. When these requirements are addressed, low-cost crop imaging can move beyond its role as a basic diagnostic technology and become an early-warning layer connecting plant physiology, digital agriculture, agricultural extension services, and timely farm-level management. Such integration could help farmers identify emerging crop stress earlier, prioritize field-level interventions, and make more informed decisions without requiring continuous access to expensive specialized equipment.

15. Declarations

Conflict of Interest: The author declares no conflict of interest.

Funding: No external funding was received for this simulation-based study.

Ethics Statement: No human participants, personally identifiable farmer information, experimental animals, or biological samples were used. Ethical approval was therefore not required for the present simulation. Appropriate institutional approval should be obtained for future experiments where required.

Data Availability: No original field dataset was used. Numerical values reported in the Results section are simulated specifically for methodological illustration.

Author Contribution: The sample author information is hypothetical and included solely to demonstrate manuscript formatting. Verified author and affiliation details must replace these placeholders before submission.

References

1. A. Kior, L. Yudina, Y. Zolin, V. Sukhov, and E. Sukhova, "RGB imaging as a tool for remote sensing of characteristics of terrestrial plants: A review," *Plants*, vol. 13, no. 9, Art. no. 1262, 2024, doi: 10.3390/plants13091262.
2. S. B. Cho, H. M. Soleh, J. W. Choi, W.-H. Hwang, H. Lee, Y.-S. Cho, B.-K. Cho, M. S. Kim, I. Baek, and G. Kim, "Recent methods for evaluating crop water stress using AI techniques: A review," *Sensors*, vol. 24, no. 19, Art. no. 6313, 2024, doi: 10.3390/s24196313.
3. A. P. Nugroho, A. Wiratmoko, D. Nugraha, S. Markumningsih, L. Sutiarto, M. A. F. Falah, and T. Okayasu, "Development of a low-cost thermal imaging system for water stress monitoring in indoor farming," *Smart Agricultural Technology*, vol. 11, Art. no. 101048, 2025, doi: 10.1016/j.atech.2025.101048.
4. M. Shoaib, S. U. Khan, H. AbdelHameed, and A. Qahmash, "Plant stress detection using multimodal imaging and machine learning: From leaf spectra to smartphone applications," *Frontiers in Plant Science*, vol. 16, Art. no. 1670593, published Jan. 2026, doi: 10.3389/fpls.2025.1670593.
5. C. Lauretti, S. Cimini, A. Zompanti, et al., "Plant stress early detection through a low-cost multispectral device: Toward safer and more sustainable agricultural practices," *iScience*, vol. 29, no. 6, Art. no. 116269, 2026, doi: 10.1016/j.isci.2026.116269.



6. A. Muhammad et al., “A comprehensive review of crop stress detection: Integrating conventional methods, advanced sensing, and machine learning,” *Frontiers in Plant Science*, 2025.
7. N. Paul et al., “Deep learning for plant stress detection: A comprehensive review,” *Computers and Electronics in Agriculture*, 2025.
8. A. V. Zubler and J.-Y. Yoon, “Proximal methods for plant stress detection using optical sensors and machine learning,” *Biosensors*, vol. 10, Art. no. 193, 2020, doi: 10.3390/bios10120193. The study is also cited in the recent multimodal plant-stress review.
9. M. Barjaktarovic et al., “Design and verification of a low-cost multispectral camera for precision agriculture application,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 17, pp. 6945–6957, 2024, doi: 10.1109/JSTARS.2024.3377104.
10. P. Nethala et al., “Techniques for canopy to organ level plant feature extraction through remote sensing,” *Remote Sensing*, vol. 16, 2024. The review discusses thermal imaging for crop water-stress monitoring and RGB-based crop characterization.
11. G. G. Coswosk et al., “Utilizing visible band vegetation indices from unmanned imaging for crop monitoring,” *Remote Sensing*, vol. 16, 2024.
12. J. Zhang et al., “Meta-analysis assessing the potential of drone remote sensing for crop-trait estimation,” *Remote Sensing*, vol. 16, no. 5, Art. no. 838, 2024.
13. A. Upadhyay et al., “Deep learning and computer vision in plant disease detection: A comprehensive review,” *Artificial Intelligence Review*, 2025.
14. Q. Zhang et al., “Research progress of spectral imaging techniques in plant phenotype analysis,” *Plants*, vol. 13, no. 21, Art. no. 3088, 2024.
15. J. Cooper et al., “Current methods and future needs for visible and non-visible imaging in plant-stress assessment,” *Frontiers in Plant Science*, 2025.