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Review Article

MULTIMODAL ARTIFICIAL INTELLIGENCE FOR EARLY PLANT STRESS PREDICTION: A REVIEW

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ABSTRACT

Plant stress is one of the primary limitations to crop growth, yield, and quality and can result from various abiotic and biotic stresses, including drought, extreme temperatures, salinity, nutrient imbalance, pathogens, and insect pests. Early detection of plant stress is crucial for enabling timely intervention and preventing potential crop losses. In recent years, the use of artificial intelligence (AI) for automated plant health assessment has gained increasing attention through image-based deep learning and sensor-based machine learning techniques. However, single-modality approaches may have limited capability to capture the complex relationships between plant visual characteristics and environmental conditions. Multimodal AI can address this limitation by integrating complementary information from visual modalities, such as RGB, thermal, multispectral, and hyperspectral imaging, with environmental indicators, including temperature, humidity, soil moisture, light intensity, and weather conditions. In AI-based plant stress assessment, with a particular focus on multimodal data fusion and early stress prediction. AI architectures, data fusion methods, datasets, sensing modalities, and explainable AI (XAI) techniques are examined in detail. Furthermore, key challenges associated with multimodal dataset collection, sensor synchronization, environmental variability, model generalization, computational requirements, and real-world deployment are discussed. Finally, promising research directions, including temporal multimodal learning, edge AI, explainable multimodal models, low-cost sensing technologies, and foundation models for plant science, are highlighted.

Keywords: Artificial Intelligence, Plant Stress, Computer Vision, Precision Agriculture

INTRODUCTION

Plant physiological functions play a critical role in the productivity of agriculture because the physiological function of plants is sensitive to any changes in environmental and biological factors. The plants are subject to different types of stresses such as drought, temperature extremes, salinity, nutrient depletion, waterlogging, diseases, and pest attack. Such factors affect plant physiology and biochemistry, thereby leading to poor yield and product quality. The growing environmental variations and demands for food production have made it necessary to monitor the condition of plants. Stress evaluation of plants involves visual inspection, scouting in fields, analysis in laboratories, and interpretation by experts. While these methods may yield valuable information, they usually prove to be laborious, subjective, time-consuming, and not easy to implement in extensive agriculture. Visible indicators such as leaves turning brown or yellow, wilting, and necrosis appear after the physiological change has taken place Zhuang et al. (2020). Artificial intelligence has presented novel ways to automate the process of assessing the health of plants using automated and non-

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destructive means. The use of machine learning and deep learning algorithms has been used to derive patterns from images and sensor data from plants without the need for hand-crafting features. In computer neural networks have found extensive study in their ability to detect images of plant phenotyping and disease/stress Guo et al. (2024). On deep learning for plant phenotyping have pointed out the increasing uses of deep learning methods in plant phenotyping and imaging-based stress detection, but there are still problems with data and sensor standardization. Visual sensing gives an indication of the physiological status of the plant. RGB sensing is capable of detecting the color, form, texture and morphology changes in leaves, while thermal sensing may detect any temperature variations related to the water content of the plants. Multispectral and hyperspectral sensing may give further information on the physiological and biochemical status of the plant that cannot be detected using RGB sensing. Appearance of plants by itself may not provide enough information to diagnose the causes and early stages of stress. Environmental variables such as moisture, temperature, relative humidity, and light intensity affect plant physiology directly. Therefore, environmental sensing can provide information about the situation, which can be used along with visual data for diagnostic purposes. Combining information from multiple sources may allow AI models to achieve a more complete description of the state of plants compared to models working with one modality Grunig et al. (2021). It has resulted in growing popularity of multimodal AI, which means combination of information provided by two or more complementary data sources inside one learning system. It can be based on RGB and thermal images, hyperspectral data and environmental sensors, or images of plants and IoT-based sensor data. Due to huge variety of plant species, types of stress, sensor types, used datasets and evaluation criteria, to consider is that of the difference between the detection of stress and the prediction of stress. While traditional AI systems normally rely on classification once the symptom has appeared, early prediction involves the ability to determine when the plant starts to experience stress and how it develops. This involves taking into account the temporal aspect of environmental patterns, temporal aspects of plant observation, and physiological change over time. However, explain ability is becoming increasingly important in AI-assisted plant science. Moderate stress for instance, does not carry much meaning by itself, it might help to know which factors led to such an assessment and there are several explainable AI techniques available, like Grad-CAM, SHAP, and attention visualization and there are still some issues that have not yet been addressed. Multimodal systems will require a dataset that is both synchronized and large enough to have complementary information. Changes in lighting conditions, sensors used, types of crops, developmental stages, environmental settings, and field backdrops could affect the performance of the model. Moreover, high-resolution imaging systems and AI frameworks will increase the cost of implementation. The current status of multimodal AI in the prediction of stress at an early stage for plants, and especially in terms of the combination of visual and environmental data Butte et al. (2021). It addresses different sensor modalities, architectures of AI, data fusion techniques, datasets, explain ability methods, and assessment methods.

LITERATURE REVIEW

Stress may have an adverse effect on the process of photosynthesis, water relations, nutrient acquisition, cellular metabolism, and growth in general. Plant stress can be categorized as either abiotic or biotic stress depending on the cause of the stress. High-throughput phenotyping and machine learning for plant stress phenotyping indicate that ground-based imaging, aerial platforms, and remote sensing techniques can be useful in obtaining large-scale information about plant responses to biotic and abiotic stresses Gill et al. (2022). Data obtained from such high-throughput systems is voluminous and poses challenges for efficient data processing and analysis. Lower levels of soil moisture can lead to stomata closure, decreased transpiration, and low rate of photosynthesis, leaf rolling, wilting, and plant growth. It means that soil-moisture sensing techniques and imaging can indicate water deficiency early enough. Multimodal data fusion for water stress classification in sweet potato crops with the help of RGB thermal images along with growth parameters and the use of multiple image modalities could be used to classify different stages of water stress Choi et al. (2025). Wen et al. (2023) explained thermal imaging for high-throughput plant phenotyping and reported that abiotic stress can influence transpiration and consequently alter leaf temperature. High temperature may cause damage to membranes, enzyme functioning, photosynthesis, and water relations, while low temperature affects metabolism and other cellular processes. The salinity levels in the soil can affect the water and mineral uptake process, causing stunted growth, chlorosis, and damage to leaves. There is environmental information that can be obtained from soil tests Walsh et al. (2024). Nutrient deficiency may cause changes in color, form, growth rate, and biomass of leaves. Chlorosis and malformation of leaves are typical symptoms of nutrient imbalance. Numerous applications of computer vision and deep learning in the detection and classification of these signs such as lesions, spots, discoloration, distortion, wilting, among others diseases in plants. Lowe et al. (2017) have looked into hyperspectral image analysis methods to detect and classify plant diseases and stress. That hyperspectral data could be able to identify the spectral differences due to plant stress which could not be easily observed by RGB images. The growing number of data collected using digital imaging techniques and sensors has paved the way for Artificial Intelligence to facilitate plant stress detection. Gill et al. (2022) explored machine learning and deep learning approaches for high-throughput plant stress phenotyping and pointed out that machine learning can turn big phenotyping data sets into valuable information for stress characterization. Deep learning alleviates the reliance on handcrafted features through the direct learning of representations from the input data. Murphy et al. (2024) indicated that deep learning can be used to automate the process of extracting useful plant traits through high throughput image data is essential in developing models. Paul et al. (2025) performed a comprehensive study on deep learning techniques used in the detection of plant stress and studied aspects of image acquisition, pre-processing, deep learning structures, and its application in stress classification, disease detection, and segmentation. Some of the problems highlighted were datasets, environmental variation, and generalization.

Deep learning in image-based plant phenotyping and it models have the ability to extract valuable information from many plant images automatically, thus minimizing the need for the handcrafting of image features Murphy et al. (2024). a trained deep-learning model can be fine-tuned for particular stress-related plant classification tasks. This is especially helpful in scenarios where agronomic datasets have limited labelled images. Paul et al. (2025) recognized transfer learning and other data-efficient learning techniques as being beneficial in dealing with limited labeled datasets in plant stress detection. Environmental conditions provide complementary information about the state of the plant such as Environmental cue relevance to plant stress, Soil moisture indicates water availability, Temperature influences metabolic and physiological processes, Soil electrical conductivity provides information related to salinity, CO_2 concentration influences photosynthetic activity and Rainfall influences water availability. AI algorithms could be able to differentiate among stress conditions that may look similar visually and recognize changes in the environment responsible for the stress onset Walsh et al. (2024). RGB imagery gives morphological information, thermal imagery provides data regarding temperatures and transpiration rates, and spectral imagery gives wavelength-dependent information, while environmental sensors give environmental information. For instance, reduced soil moisture may suggest water deficit, whereas an increase in leaf temperature may suggest changes in transpiration rate. If all these data are observed together with changes in morphology from RGB images, then the results may show strong evidence for water stress more effectively. Choi et al. (2025) proposed a Vision Transformer CNN approach to classify water stress levels in sweet potatoes using RGB and thermal images. The outcome revealed that a combination of CNNs for feature extraction and transformers for representation learning could be useful in multimodal stress classification.

Multi-modal AI is an AI that involves multiple, complementary data modes within one learning paradigm. Within stress evaluation of plants, those modes may include RGB images, thermal images, multispectral or hyperspectral images, and sensor data for the environment. Each sensing modality represents the plant state differently. RGB gives information on visible morphological state, thermal imaging gives temperature information, spectral imaging provides wavelength-specific information, and environmental sensors give contextual information. Patil et al. (2026) to explore the use of multimodal AI to detect stress in different plant species and shows the increasing applications of multimodal learning in the area of stress detection in plants. However, there is also a need for synchronization, calibration, more storage, and computation in multimodal systems. Shoaib et al. (2026) conducted the application of multimodal imaging and machine-learning techniques, from leaf spectra to smartphone-enabled systems and emphasized the complementing nature of optical sensing techniques and machine learning in stress detection in plants. Wen et al. (2023) shows that thermal imaging is useful in providing quick and non-destructive data on plant growth and stress responses. Its possible use in detecting diseases early as pathogen infection affects thermal energy dissipation. Lowe et al. (2017) shows the possible use of hyperspectral imaging technology in detecting and classifying plant diseases and stresses. It can identify small changes in the spectrum related to physiological processes that cannot be seen in normal RGB images. The environmental sensors give information regarding the surroundings of the plants. The integration of measurements taken from the environment with images allows for temporality in the identification of environmental changes preceding symptoms. Interpretability is critical as the complexity of AI models increases in agriculture. Mostafa et el. (2023) has explainable deep learning in plant phenotyping and emphasized the need for interpretability in deep learning predictions.

Based on the literatures to develop a robust and explainable multimodal framework for early plant-stress prediction. The specific objectives are to acquire and synchronize RGB, thermal, spectral, and environmental sensor data; develop effective multimodal feature extraction and fusion techniques; model temporal patterns to predict stress progression at an early stage; determine stress type, severity, and probability; improve model robustness across diverse crops and environmental conditions; provide interpretable evidence for model predictions using explainable AI; and generate timely alerts to support appropriate agricultural interventions.

EXPERIMENTAL WORK

Figure 1

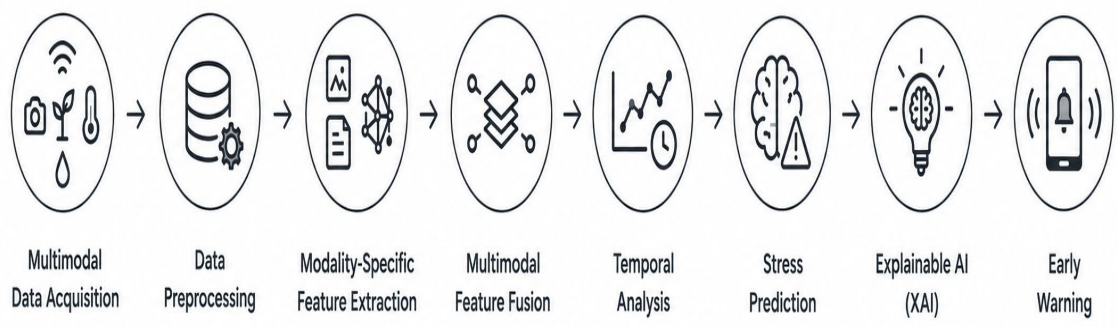


Figure 1 Multimodal AI Early Plant Stress Prediction Processes

In Figure 1 Multimodal data acquisition stage involves collecting complementary data from plants and their surrounding environment to obtain a comprehensive representation of plant health. The framework uses visible RGB imagery for morphology, colour, shape, and texture; thermal imagery for leaf or canopy temperature; multispectral or hyperspectral imagery for spectral characteristics; and sensor measurements such as soil moisture, temperature, humidity, light intensity, and soil electrical conductivity. All measurements are timestamped to establish correspondence between different modalities and support temporal analysis. The acquired data undergo modality-specific preprocessing to improve quality and consistency. Image preprocessing includes resizing, denoising, normalization, background management, enhancement, augmentation, thermal calibration, and spectral normalization. Sensor data are processed through noise removal, missing-value handling, outlier detection, normalization, and temporal alignment. Synchronization is particularly important because plant appearance and environmental conditions change continuously over time.

Each modality is processed using a suitable feature extraction model to obtain meaningful representations. The RGB encoder captures leaf color, morphology, shape, and texture, while the thermal encoder identifies temperature-distribution patterns. The spectral encoder extracts wavelength-dependent features, and the sensor-processing network learns patterns from environmental time-series data. CNNs can be used for spatial feature extraction, while Vision Transformers can capture broader contextual and long-range relationships within image representations Mae and Steppe (2019). The extracted RGB, thermal, spectral, and sensor features are integrated using a multimodal fusion technique to create a unified plant-state representation. An attention-based fusion mechanism can dynamically assign importance to each modality depending on the stress condition. For example, thermal information may be more relevant for water stress, while spectral information can provide stronger indications of biochemical or nutrient-related changes. This approach combines complementary information while emphasizing the most informative features.

The framework analyzes the temporal evolution of plant and environmental conditions to identify patterns associated with stress development. The unified multimodal representation is processed using sequence-learning approaches such as Recurrent Neural Networks (RNNs), temporal transformers, or related temporal models. This stage enables the system to recognize persistent changes and early stress patterns that may not be evident from individual observations. The temporally analyzed representation is provided to the prediction module to determine stress status, type, severity, and probability. Stress status can be categorized as healthy, early stress, moderate stress, or severe stress. The framework can identify conditions such as drought, heat, salinity, nutrient deficiency, and biotic stress while generating probability scores for each category. This multi-output approach provides more detailed information than simple healthy/stressed classification.

The explainability module provides evidence supporting the model's predictions. For image-based predictions, Grad-CAM and attention maps can highlight relevant plant regions, while SHAP and feature-importance methods can identify influential sensor variables. For example, early water stress may be associated with changes in leaf regions, low soil moisture, and increased canopy temperature Saleem et al. (2020). This evidence improves transparency and helps users understand the basis of the prediction. The final stage converts stress predictions into timely alerts. When the probability of a stress condition exceeds a predefined threshold, the system generates an early warning indicating the likely stress condition and severity. Appropriate interventions, such as irrigation, environmental modification, fertilizer application, or disease investigation, can then be recommended. This enables timely intervention, reduces potential crop losses, and supports efficient agricultural resource management.

RESULTS AND DISCUSSIONS

In Table 1 shows the comparison highlights that different AI techniques have specific strengths and limitations for plant-stress evaluation. Traditional methods such as SVM and Random Forest are effective for structured sensor and environmental data but have limited representation-learning capabilities. CNNs and Transfer Learning are well suited for image-based stress detection, although they depend on adequate training data and may be affected by domain variations. Vision Transformers can capture global relationships in complex images but require greater computational resources. Multimodal Transformers provide a promising approach for integrating complementary RGB, thermal, spectral, and sensor information, making them particularly suitable for comprehensive and early plant-stress prediction.

Table 1

Table 1 Comparison of different AI techniques Hernanda et al. (2024) Lassalle (2021)

AI approach	Strength	Limitation	Suitable Application
SVM	Effective for structured features	Requires feature engineering	Sensor and spectral features
Random Forest	Robust and relatively interpretable	Limited representation learning	Environmental data

CNN	Strong spatial feature extraction	Requires sufficient training data	RGB and thermal images
Transfer Learning	Useful with limited labelled data	Domain-shift sensitivity	Plant image classification
Vision Transformer	Captures global relationships	Higher computational demand	Complex image analysis
Multimodal Transformer	Integrates multiple modalities	Requires synchronized multimodal data	Multimodal stress prediction

The Table 2 summarizes the complementary roles of different sensing modalities in plant-stress assessment. RGB imagery provides accessible information on visible plant characteristics, while thermal, multispectral, and hyperspectral data offer additional physiological and spectral information that can reveal stress-related changes not easily observed visually. Soil moisture, temperature, humidity, and electrical conductivity (EC) provide important environmental and soil conditions influencing plant health. Although each modality has limitations such as environmental sensitivity, localized measurements, calibration requirements, or higher equipment costs, their integration can provide a more comprehensive and reliable representation of plant stress than relying on a single modality.

Table 2

Table 2 Different sensing modalities in plant-stress assessment Singh et al. (2015) Ferentinos (2018)

Modality	Main information	Major advantage	Major limitation
RGB	Color, shape, texture	Low cost and accessible	Limited early physiological information
Thermal	Leaf/canopy temperature	Physiological information	Sensitive to environmental conditions
Multispectral	Selected spectral bands	Vegetation and physiological information	Specialized sensor required
Hyperspectral	Detailed spectral signature	Sensitive to subtle changes	High data and equipment requirements
Soil moisture	Water availability	Direct environmental indicator	Localized measurement
Temperature	Environmental thermal condition	Easy continuous monitoring	Environmental variability
Humidity	Atmospheric moisture	Useful for transpiration context	Calibration required
EC	Soil salinity	Salinity-related information	Soil dependent

Single-modality AI relies on a single source of information, such as RGB imagery, thermal imagery, or sensor data, making it relatively simple and computationally efficient but potentially limited in detecting complex and early-stage plant stress. In contrast, multimodal AI combines complementary information from multiple sources, such as RGB, thermal, multispectral/hyperspectral imagery, and environmental sensors. This integration enables the model to capture both visible and physiological changes, improve stress discrimination, and provide more comprehensive predictions. Although multimodal AI requires greater computational resources and effective data synchronization, it offers greater potential for robust, explainable, and early plant-stress prediction under diverse environmental conditions.

Early stress prediction focuses on identifying physiological changes in plants before visible symptoms become severe. Unlike conventional approaches that mainly classify already-developed stress conditions, the proposed framework integrates multimodal data and temporal patterns from RGB, thermal, spectral, and environmental sensors to detect gradual changes in plant health. By analyzing these changes over time and generating stress probabilities, the system can identify emerging conditions such as drought, heat, salinity, nutrient deficiency, and biotic stress at an early stage. This capability enables timely interventions, reduces potential crop losses, and supports efficient agricultural resource management.

Explainability and reliability are essential for the practical adoption of AI-based plant-stress prediction systems. Explainable AI (XAI) techniques such as Grad-CAM, attention maps, and SHAP can identify the image regions, spectral characteristics, or environmental factors that influence a prediction. Reliability can be improved by integrating complementary modalities, temporal

information, confidence scores, and validation across different crops and environmental conditions. By linking predictions to observable plant and environmental evidence, the proposed framework can improve transparency, user trust, and decision-making, while supporting more dependable early-warning and intervention strategies.

Real-world deployment of multimodal plant-stress prediction systems involves several practical challenges. The comprehensive datasets covering multiple modalities, crop species, stress types, and growth stages are still limited. Different sensors operate at varying sampling rates and spatial resolutions, making accurate temporal synchronization essential. Models trained under controlled greenhouse conditions may have limited generalization to diverse open-field environments. Processing and storing high-resolution RGB, thermal, multispectral, and hyperspectral data can require substantial computational and storage resources. Then sensor failures, communication interruptions, and environmental interference may result in missing data, requiring robust multimodal models that can maintain reliable predictions even when one or more modalities are unavailable.

Future research should focus on developing temporal and adaptive multimodal systems that analyze sequential plant and environmental observations to identify stress progression at an early stage. The development of lightweight multimodal models can enable real-time processing on edge devices, reducing dependence on cloud connectivity and computational infrastructure. Integrating low-cost RGB cameras with affordable environmental sensors can further improve accessibility for small-scale farmers. Future models should also provide explainable predictions by identifying the modalities and specific features contributing to each stress assessment. Finally, extensive validation across different crop species, growth stages, geographical regions, weather conditions, and agricultural environments is required to establish model robustness and generalization.

CONCLUSION

In this paper presents a robust and explainable multimodal AI framework for early plant-stress prediction by integrating RGB, thermal, multispectral, and environmental sensor data. Unlike conventional approaches that primarily rely on visible symptoms, the framework combines complementary plant, soil, and environmental information with temporal analysis to identify stress-related changes before severe symptoms become visible. Modality-specific feature extraction and multimodal fusion enable comprehensive representation of plant health, while explainable AI techniques provide interpretable evidence for predictions. The objective to determine stress type, severity, and probability and generate timely alerts to support appropriate agricultural interventions. Addressing challenges such as data synchronization, environmental variability, computational requirements, and cross-environment generalization can improve its practical reliability. The potential to support timely, data-driven crop management, reduce crop losses, optimize agricultural resources, and contribute to more efficient and sustainable farming practices.

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