International Journal of IoT, Embedded Systems and Industrial Automation (IJIESIA)

April-June-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/n9fxpp10

Article - e004

AI Camera Sensor-Based Detection of Crop Water Stress and Pesticide Requirement

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Received: 05/04/2026 **Revision Received**: 01/05/2026 **Accepted**: 07/05/2026

ABSTRACT

Artificial intelligence (AI)-enabled camera sensor systems are increasingly transforming precision agriculture by providing non-destructive, rapid, and scalable methods for monitoring crop health. Two of the most critical applications are the detection of crop water stress and the assessment of pesticide requirement through pest, disease, and symptom recognition. This literature review synthesizes published work on RGB, thermal, multispectral, and hyperspectral imaging integrated with machine learning and deep learning methods for agricultural decision support. The reviewed studies show that thermal and hyperspectral imaging are particularly effective for water stress detection, whereas RGB and multispectral systems are highly practical for identifying disease symptoms, pest infestation, and spray targets. The literature further indicates a shift from simple classification toward real-time decision support, multimodal fusion, explainable AI, and precision input application. This review discusses core sensing technologies, major algorithmic approaches, research findings from key studies, present limitations, and future research directions. Overall, AI camera sensor systems offer substantial potential for reducing water wastage, minimizing excessive pesticide use, and improving sustainable agricultural productivity.

KEYWORDS: Precision Agriculture, AI Camera Sensor, Crop Water Stress, Pesticide Requirement, Thermal Imaging, RGB Imaging, Hyperspectral Imaging, Deep Learning, Computer Vision

1. Introduction

Contemporary farming is moving toward advanced monitoring frameworks designed to identify crop stress early and facilitate prompt corrective measures. Issues like water deficit and inefficient chemical usage are critical priorities, as they directly impact crop yield, economic returns, and ecological health. Conventional manual scouting is often slow, physically demanding, and prone to human error. Conversely, camera-based AI systems provide a consistent, non-invasive, and scalable alternative for overseeing expansive farmland. Current research underscores that image-driven phenotyping is now a primary field for detecting both environmental (abiotic) and biological (biotic) stressors. A series of key studies have shaped this landscape:

Cho et al. (2024): Demonstrated that while RGB, thermal, and hyperspectral imaging are all viable for assessing water stress, thermal and hyperspectral sensors offer superior sensitivity for non-destructive observation. This work is pivotal for linking various sensing platforms with complex AI techniques—including deep learning, ensemble methods, and explainable AI—to enhance irrigation decisions. Walsh et al. (2024): Positioned camera-based AI as a cohesive framework capable of recognizing diverse threats, ranging from drought to pathogen infestations. Notably, they identified a shift toward regression-based modeling after 2021, emphasizing that real-world applications require quantifying stress severity rather than just binary "healthy or unhealthy" labeling.

Paul et al. (2025): Noted that while most models rely on affordable RGB data, integrating multimodal inputs like temperature or humidity significantly boosts performance in complex field environments where symptoms might overlap. Their analysis helps explain the gap between successful lab results and the challenges of actual farm implementation.

Mahlein (2016): Provided a foundational basis for using optical sensors to detect disease-related physiological changes that are invisible to the naked eye. This work established the core concepts for integrating imaging sensors into precision health diagnostics. Collectively, these contributions confirm that AI-powered camera sensors have become essential tools for modern precision agriculture, specifically for managing water resources and providing data-driven support for pesticide applications.

2. Methodology for Literature Selection

This review paper was prepared through a systematic study of recent research related to AI-based camera sensor technologies used in precision agriculture. The primary focus was on crop water stress detection and pesticide requirement assessment using image-processing and deep learning techniques.

Relevant research articles were collected from well-known scientific platforms such as Google Scholar, ScienceDirect, IEEE Xplore, SpringerLink, MDPI, and Frontiers. Different keyword combinations were used during the literature search process, including terms such as “AI in agriculture,” “crop water stress detection,” “thermal imaging,” “plant disease

April-June-Issue, Vol. 1, No. 1 (2026) | DOI: 10.66261/n9fxpp10

detection," "precision spraying," "deep learning for agriculture," and "computer vision in farming."

The review mainly considered peer-reviewed journal articles published between 2016 and 2025. Studies were selected if they focused on:

- AI, machine learning, or deep learning applications in agriculture,
- Camera sensor technologies such as RGB, thermal, multispectral, or hyperspectral imaging,
- Crop stress detection, disease identification, pest monitoring, or pesticide-related decision support.

Papers without imaging-based techniques, duplicate studies, and articles lacking sufficient technical information were excluded. After detailed screening and analysis, the selected literature was grouped into categories including sensing technologies, AI methods, water stress monitoring, pesticide-related applications, research trends, and future challenges.

This approach helped ensure that the review covered both foundational studies and recent advancements in AI-enabled agricultural monitoring systems

Table: Summary of Major Studies Reviewed

Study	Sensor Technology	AI Technique	Main Application	Important Findings
Cho et al. (2024)	Thermal & Hyperspectral Imaging	Machine Learning and Deep Learning	Crop water stress detection	Thermal and hyperspectral imaging showed strong performance for stress monitoring
Walsh et al. (2024)	RGB and Multi-sensor Imaging	AI-Based Phenotyping Model	Plant Stress Analysis	Regression models improved stress severity estimation
Paul et al. (2025)	RGB + Environmental Data	Deep Learning	Plant Stress Detection	Multimodal data improved prediction accuracy
Mahlein (2016)	Optical Imaging Sensors	Image Analysis Techniques	Disease Detection	Optical Sensing can detect invisible physiological changes

Zhou et al. (2021)	Thermal Infrared Imaging	Deep learning	Irrigation Monitoring	Canopy temperature effectively reflects crop water stress
Khan et al. (2025)	RGB imaging	CNN-based detection model	Plant - diseases detection	Dataset quality and diversity remain important challenges
Singh et al. (2024)	Drone-based Camera System	AI+IOT integration	Precision-pesticides Spraying	AI-guided drone support selective spraying
Dalal et al. (2025)	Multiple-imaging system	Object Detection Algorithm	Pest and weed Identification	Deep learning improved localization accuracy

3. Camera Sensor Technologies Used in AI-Based Crop Monitoring

3.1 RGB Cameras

RGB cameras are the most widely used devices in agricultural AI because they are inexpensive, easily deployable, and compatible with smartphones, drones, and fixed monitoring systems.

Paul et al. (2025) observed that most deep learning models for plant stress detection have been built primarily on RGB datasets. This dominance is due to the practical advantage of RGB images in capturing visible disease lesions, discoloration, wilting, pest damage, and weed patterns. However, the same review also noted that RGB-only systems may be less effective in capturing early physiological stress before visible symptoms appear.

Walsh et al. (2024) similarly found that RGB imaging remains a central component of image-based phenotyping because of its accessibility and strong compatibility with AI models for object detection, classification, and segmentation. For pesticide-related applications, this is especially useful because many pest and disease symptoms first become actionable when leaf surfaces, fruits, or stems show visible markers that RGB cameras can record.

3.2 Thermal Infrared Imaging

Thermal cameras are particularly important for water stress detection because plants under water deficit typically experience reduced transpiration, which can elevate canopy temperature.

Cho et al. (2024) reported that thermal imaging has high value for evaluating crop water stress in a non-destructive and timely manner. Their review placed strong emphasis on the importance of thermal signals in stress diagnosis and linked them with AI techniques for improved interpretation.

Zhou et al. (2021), in their review on crop water stress assessment using infrared thermal imagery, explained that thermal methods are strongly associated with canopy temperature mapping and crop water stress index-based analysis. Their contribution is essential because it systematically connected thermal sensing to precision irrigation and also discussed the future role of deep learning in interpreting thermal stress patterns. This paper is one of the most important references for the water stress portion of the present literature review.

3.3 Multispectral and Hyperspectral Imaging

Multispectral and hyperspectral imaging provide information outside the visible range, making them highly useful for detecting subtle plant physiological and biochemical changes before clear visual symptoms emerge.

Cho et al. (2024) concluded that hyperspectral imaging has strong potential for non-destructive crop water stress evaluation because it captures richer spectral signatures than RGB systems.

Mahlein (2016) also highlighted that advanced imaging systems can detect disease-associated changes that are difficult to perceive visually, which supports the use of spectral imaging for early disease and stress diagnosis. Although her discussion focused more broadly on disease sensing, the conceptual argument strongly supports later developments in AI-based pesticide requirement analysis.

3.4 Integrated Sensing Platforms

AI camera sensors are now deployed on multiple platforms including handheld devices, fixed ground stations, tractors, field robots, and UAVs.

Walsh et al. (2024) emphasized that image-based plant stress detection is increasingly connected with advanced imaging platforms and automated phenotyping systems. This is significant because deployment context affects model performance, spatial coverage, cost, and decision speed.

3.5 Sensor Configurations in Agricultural AI Systems

Different sensor configurations are used in agricultural AI systems depending on the monitoring environment, crop type, and application requirements.

RGB cameras are the most commonly used sensors because they are affordable, easy to deploy, and compatible with smartphones, drones, and field-monitoring systems. These cameras are highly useful for detecting visible symptoms such as discoloration, pest damage, and leaf diseases.

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Thermal cameras are mainly used for crop water stress monitoring because plant temperature changes are closely related to transpiration and moisture conditions. These sensors are often mounted on drones or UAV platforms to monitor large agricultural fields efficiently.

Multispectral and hyperspectral sensors provide information beyond the visible spectrum and are useful for detecting early physiological stress before visible symptoms appear. Although hyperspectral systems provide highly detailed information, they are generally more expensive and computationally demanding.

Recent agricultural AI systems increasingly combine multiple sensors such as RGB cameras, thermal imaging devices, humidity sensors, and soil moisture sensors to improve detection accuracy and reliability under real-world farming conditions.

4. AI and Deep Learning Methods for Stress Detection

4.1 Machine Learning

Traditional machine learning models in agricultural imaging often rely on handcrafted features derived from color, texture, temperature, or reflectance. **Cho et al. (2024)** showed that machine learning continues to be relevant for crop water stress prediction, especially in contexts with limited data. Their review discussed how machine learning can be combined with multiple sensing types for predictive analysis in drought-related applications.

4.2 Deep Learning

Deep learning has become the dominant framework for image-based crop monitoring due to its strong feature extraction ability. **Paul et al. (2025)** stated that deep learning-based systems have emerged as powerful methods for plant stress diagnosis because they can automatically learn informative features from images rather than depending solely on manually designed descriptors. They further argued that custom-designed architectures can sometimes outperform general-purpose transfer learning systems for specific plant-stress combinations.

Walsh et al. (2024) also emphasized that modern AI-applied algorithms are expanding beyond simple classification and now include regression, segmentation, and more flexible plant-response prediction methods. This is especially relevant for field use because the farmer often needs severity estimates, not only class labels.

4.3 Multimodal and Data-Efficient AI

A major theme in recent literature is the need to combine image data with other contextual inputs. **Paul et al. (2025)** noted that multimodal inputs such as image, temperature, and humidity can improve prediction accuracy. They also discussed self-supervised learning and few-shot learning as important methods for addressing the scarcity of labeled agricultural datasets. These insights are particularly valuable when designing practical systems for small farms or region-specific crops where large annotated datasets may not exist.

4.4 AI-Based Agricultural Monitoring Workflow

AI camera sensor-based agricultural monitoring systems generally follow a multi-stage workflow for crop analysis and agricultural decision support. The overall process combines sensing technologies, image processing, and artificial intelligence techniques to monitor crop conditions in real time.

Initially, images are captured using RGB, thermal, multispectral, or hyperspectral cameras mounted on drones, tractors, robots, handheld devices, or fixed monitoring platforms. Different sensor types are selected depending on the target application such as water stress monitoring, disease detection, or pesticide requirement assessment.

The captured images are then preprocessed to improve quality and ensure consistency. Common preprocessing operations include image resizing, normalization, noise removal, contrast enhancement, and segmentation of plant regions from the background environment. These steps help improve the performance of machine learning and deep learning models.

After preprocessing, AI-based algorithms analyze the images to identify crop stress symptoms, disease patterns, pest infestation, temperature variation, or irrigation-related indicators. Depending on the application, the system may use classification, object detection, segmentation, or regression models for prediction and analysis. Deep learning architectures such as convolutional neural networks (CNNs) are widely used because of their strong feature extraction capability.

Finally, the generated output is converted into practical agricultural recommendations such as irrigation scheduling, disease warning, pesticide spraying decisions, or precision farming actions. In modern precision agriculture, these recommendations may also be integrated with drones, IoT devices, or automated spraying systems for real-time field intervention.

This workflow demonstrates how AI camera sensor systems support efficient crop monitoring while reducing unnecessary water usage, excessive pesticide application, labor requirements, and environmental impact

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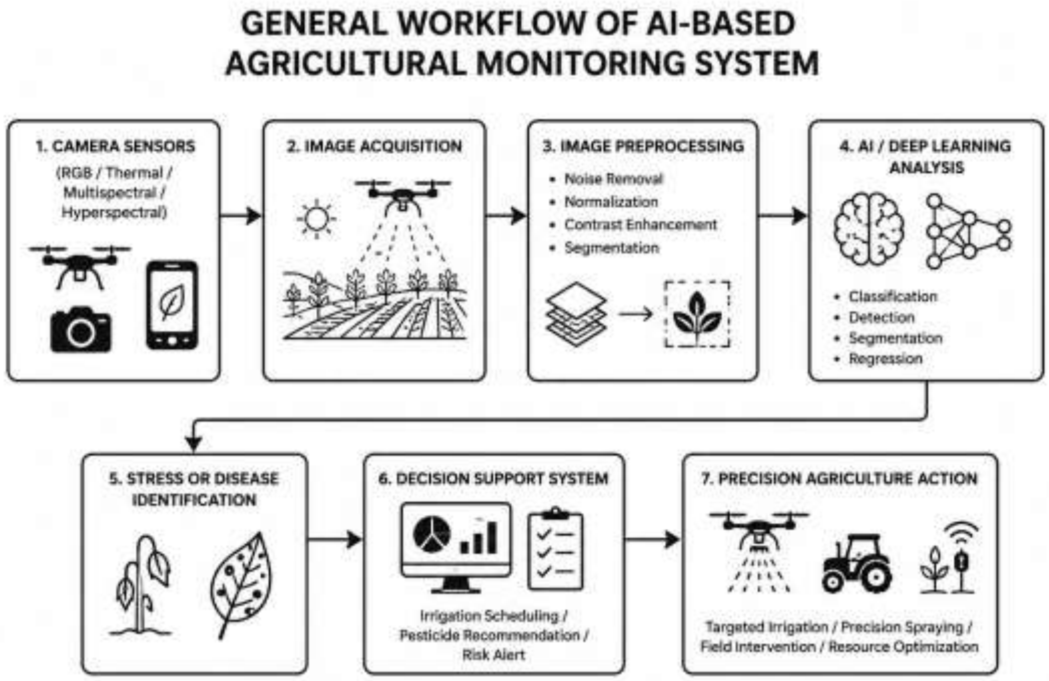

5. Literature on AI Camera Sensor Detection of Crop Water Stress

The literature clearly shows that crop water stress detection is one of the strongest application areas of AI camera sensing. **Cho et al. (2024)** directly focused on this topic and found that different remote sensing platforms have complementary strengths. Their review concluded that thermal imaging and hyperspectral imaging are especially promising for crop water stress evaluation, while AI methods enhance interpretation accuracy and scalability. This study therefore provides the central evidence base for the idea that AI camera sensors can support irrigation management.

Zhou et al. (2021) reinforced this conclusion by reviewing infrared thermal imagery for crop water stress assessment in precision agriculture. They explained that canopy temperature reflects plant water status and that thermal approaches are valuable for deep learning-based monitoring. Their work is important because it bridges physiological interpretation with image analysis and identifies thermal imaging as one of the most direct pathways for non-contact drought detection.

Walsh et al. (2024) broadened the perspective by positioning water stress within the wider family of plant stress responses addressed by AI imaging. Their study highlighted that regression approaches have seen increased use since 2021, which is particularly meaningful for water stress because irrigation decisions depend on stress intensity, not merely its presence.

Paul et al. (2025) contributed to the water stress discussion by showing that training data from diverse growth settings are necessary for generalizable deep learning systems. They also warned that overlapping stress symptoms can confuse AI models, which is highly relevant in drought conditions because nutrient stress, heat stress, and disease stress may create partially similar visual responses.

An empirical study often cited in this domain, "**Identifying Crop Water Stress Using Deep Learning Models" (2020),** reported that thermal imagery outperformed RGB imagery in certain water stress detection scenarios, with very high classification accuracy under the tested conditions. This study is important because it provides experimental support for the broader review-level conclusion that thermal information often carries more direct evidence of plant water deficit than visible imagery alone.

Arumugam et al. (2025) discussed the assessment of crop water stress using infrared thermal imaging and strengthened the argument that thermal-based methods are practical for irrigation-related crop monitoring. Their work supports the idea that temperature-derived plant indicators can be integrated into AI frameworks for water stress evaluation.

Together, these studies show that AI camera sensor-based water stress detection is moving from academic experimentation toward operational irrigation support systems. However, they also indicate persistent challenges related to environmental variation, calibration, crop-specific response, and cross-field transferability.

6. Literature on AI Camera Sensor Detection for Pesticide Requirement

Unlike water stress, pesticide requirement is rarely measured directly. Instead, image-based systems estimate pesticide need by identifying disease symptoms, pest presence, infestation severity, weed pressure, or spatial target distribution. For this reason, the literature on pesticide requirement is closely linked with plant disease detection, pest monitoring, and precision spraying.

Mahlein (2016) is a foundational reference in this area because she explained how imaging sensors can support plant disease diagnosis through non-destructive detection of stress-related patterns. Her study showed that optical sensing is not limited to visible lesion inspection but can reveal broader disease-related signatures useful for precision agriculture and plant phenotyping. This paper forms a conceptual base for image-guided pesticide decisions.

Paul et al. (2025) added a deep learning perspective by reviewing plant stress detection technologies across multiple stress categories. Their analysis is relevant for pesticide requirement because it shows how image classification, segmentation, and multimodal learning can help distinguish plant disorders that may call for intervention. At the same time, they also cautioned that overlapping stress symptoms remain a major challenge, which is important because not every visible symptom requires pesticide use.

Walsh et al. (2024) supported the integration of biotic and abiotic stress analysis within AI-based imaging systems. This is highly relevant because incorrect pesticide application can occur when water stress or nutrient deficiency is mistaken for disease. Their review therefore indirectly supports more careful, integrated decision support rather than single-symptom pesticide recommendations.

Khan et al. (2025), in a review on automated plant disease detection, discussed motivations, open challenges, datasets, and future trends in AI-based disease recognition. This study is especially useful in the pesticide context because disease identification is often the first step toward deciding whether spraying is needed. Their review also underscores the importance of reliable datasets and field realism for building trustworthy systems.

Mamabolo et al. (2025) examined precision agriculture technologies for crop monitoring and early detection of stress, disease, and pests. Their work contributed to the present review by showing that early detection technologies can support timely intervention and reduce unnecessary chemical input. This supports the broader sustainability argument of AI-guided pesticide management.

Ghazal et al. (2024) reviewed computer vision in smart agriculture and precision farming and highlighted the significance of object detection and image analysis for agricultural monitoring tasks. Their work is relevant because pesticide requirement increasingly depends on locating the exact area or plant organ that needs treatment rather than blanket field-wide spraying.

Dalal et al. (2025) reviewed deep learning-based object detection in agriculture and showed the growing importance of detection frameworks for identifying agricultural targets in operational environments. In pesticide applications, this is important for detecting pests, weeds, or diseased zones that may be selectively sprayed instead of treating entire fields uniformly.

Singh et al. (2024) described a smart agriculture drone for crop spraying using image-based AI and IoT. This study is practically important because it represents the transition from simple symptom recognition to active, image-guided field intervention. It supports the view that AI camera sensors are not only diagnostic tools but also operational tools for precision spraying.

Overall, these studies suggest that image-based pesticide requirement systems currently function best as decision-support tools rather than fully autonomous agronomic prescription engines. They can indicate where stress, disease, or pest symptoms occur and help localize treatment, but exact pesticide dosage still requires agronomic rules, crop stage information, weather considerations, and label-based recommendations. This conclusion is an inference drawn from the literature because most reviewed papers focus more on detection accuracy than on pesticide dose optimization.

7. Additional Supporting Literature Integrated into the Review

To strengthen the broader understanding of this field, several additional review-oriented studies are important.

Zhang et al. (2025) presented a bibliometric review of deep learning in crop monitoring and helped demonstrate that AI-based agricultural imaging is a rapidly expanding field with increasing methodological diversity. This paper contributes trend-level evidence to the present review.

The 2024 early detection review on precision agriculture technologies for stress, disease, and pest monitoring reinforced the importance of thermal and spectral sensing for early crop problem identification. It was useful in supporting the argument that early stress detection can reduce resource waste and improve intervention timing.

The 2025 Frontiers review on comprehensive crop stress detection further supports the integrated understanding that crop stress analysis increasingly requires multimodal sensing, robust data pipelines, and practical field applicability. This paper helped frame the present discussion of future directions.

These additional sources were not the sole basis of any one section, but they were used to reinforce the consistency of major trends across the literature.

8. Major Research Trends

A clear trend in the literature is the movement from simple recognition systems toward actionable agricultural decision support. **Cho et al. (2024)** and **Zhou et al. (2021)** point toward irrigation-focused water stress analytics, while **Singh et al. (2024)** indicates progress toward AI-guided spray operations. **Paul et al. (2025) and Walsh et al. (2024)** together show that modern AI systems are evolving toward multimodal, efficient, and severity-aware modeling rather than narrow image classification alone.

A second trend is the growing recognition that no single sensor type is sufficient across all applications. RGB imaging remains dominant because of affordability and dataset abundance, but thermal and hyperspectral imaging often provide more informative signals for early or physiologically grounded stress detection. This conclusion is strongly supported by **Cho et al. (2024)** and conceptually aligned with **Mahlein (2016)**.

A third trend is the increasing importance of real-world deployment. **Paul et al. (2025)** emphasized offline usability and robustness under different growth conditions, while **Walsh et al. (2024)** highlighted broad imaging-AI progress for field-relevant plant stress analysis. These findings suggest that future research will focus more heavily on edge AI, generalization, and interpretable systems.

9. Real-World Deployment Challenges

Although AI camera sensor technologies have shown promising results in agricultural research, several challenges still affect their large-scale practical deployment.

One major issue is environmental variability. Field conditions such as changing sunlight, shadows, dust, wind, and temperature fluctuations can influence image quality and reduce model accuracy. AI systems trained under controlled laboratory conditions may not always perform consistently in real farm environments.

Another important challenge is the limitation of agricultural datasets. Many existing datasets are collected for specific crops or regions and may not represent diverse farming conditions. As a result, AI models sometimes struggle to generalize across different climates, crop varieties, and growth stages.

Hardware cost is also a practical concern. Advanced thermal and hyperspectral imaging systems are often expensive and may not be affordable for small-scale farmers. Similarly, drone-based monitoring systems require battery power, maintenance, and technical expertise.

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Internet connectivity can also become a limitation in rural agricultural regions where stable network access is not always available. This creates difficulties for cloud-based AI systems and increases the importance of offline or edge-AI solutions.

In addition, many deep learning systems operate as "black-box" models, making their predictions difficult to interpret for farmers and agricultural experts. Practical agricultural recommendations often require transparent and explainable decision-making.

Finally, AI systems alone cannot fully replace agronomic expertise. Accurate irrigation and pesticide recommendations also depend on weather conditions, crop growth stage, soil properties, and local agricultural practices. Therefore, future systems must integrate AI predictions with agronomic knowledge for reliable field deployment.

10. Research Gaps

The literature still contains several important gaps. First, many studies analyze either water stress or disease-related stress in isolation, whereas field conditions often involve multiple overlapping stresses. **Paul et al. (2025)** explicitly noted the challenge of overlapping symptoms, and this remains a major obstacle for reliable pesticide decisions and irrigation advice.

Second, most existing studies focus on detection or classification rather than the direct estimation of agronomic action quantity. Water stress papers often stop at stress identification instead of predicting exact irrigation amount, while pesticide-related studies often detect disease or pest targets without recommending validated dosage. This gap emerges from comparing the aims of **Cho et al. (2024), Mahlein (2016), and Singh et al. (2024).**

Third, many published datasets are limited by controlled conditions, crop specificity, or narrow environmental variability. **Paul et al. (2025)** and **Khan et al. (2025)** both reinforce the need for more realistic and diverse datasets to improve generalization.

Fourth, there is still insufficient integration between camera sensor systems and agronomic rule-based advisory systems. Future work should combine imaging, weather, soil moisture, growth stage, and management thresholds to produce farmer-ready recommendations rather than only AI model predictions.

11. Conclusion

The reviewed literature clearly demonstrates that AI camera sensor technologies are becoming central tools in precision agriculture. **Cho et al. (2024) and Zhou et al. (2021)** show that thermal and hyperspectral sensing are especially powerful for crop water stress monitoring, while **Mahlein (2016), Khan et al. (2025), Ghazal et al. (2024)**, and **Dalal et al. (2025)** support the growing role of image analysis in detecting disease, pests, and treatment targets relevant to pesticide requirement. **Walsh et al. (2024)** and **Paul et al. (2025)** further show that AI is shifting the field from simple stress recognition toward more advanced, multimodal, and practical decision-support systems.

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In summary, AI camera sensor systems have strong potential to reduce unnecessary irrigation and excessive pesticide application by enabling timely, localized, and data-driven intervention. However, future progress will depend on better multimodal datasets, stronger field validation, improved interpretability, and closer integration with agronomic decision frameworks. The most promising path forward is the development of end-to-end smart agriculture platforms that connect sensing, AI analysis, and real farm action in a reliable and sustainable manner.

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