Journal of Computer Science

Research Paper

Advancements In Precision Agriculture: A Review on Image-Based Stress Detection and Predictive Yield Loss Modeling

A. Josephine and Dr. A. Subhashini

Department of Computer Science, PSG College of Arts & Science, Coimbatore, India

Article history
Received: 15 May 2025
Revised: 1 July 2025
Accepted: 1 August 2025

*Corresponding Author:
A. Josephine,
Department of Computer Science, PSG College of Arts & Science, Coimbatore, India
Email: josephinea2272@gmail.com

Abstract: Precision agriculture utilizes cutting-edge technologies to maximize the management of crops, enhance utilization of resources, and maximize yield forecasting. This study critically analyzes 53 peer-reviewed articles to evaluate advancements in image-based stress detection and yield prediction techniques for precision agriculture. The review enumerates main issues, such as image-based analysis methods, different crop stress aspects (biotic, environmental, and abiotic), and remote sensing techniques for farm monitoring. The benefits of multispectral and hyperspectral imaging for crop health monitoring are also discussed, as well as the application of deep learning and machine learning in stress detection. Prediction models for yield loss, IoT and edge computing integration, and the application of optimization algorithms to enhance predictive performance are discussed. Challenges and limitations related to data processing, scalability of the model, and real-time deployment are also discussed. The research then discusses applicable tools and techniques, followed by extensively investigating the upcoming trends and opportunities. The discussion presents the possibility of integrating remote sensing, artificial intelligence-based analytics, and IoT technologies towards more accurate agriculture. The result is of great use to the researchers and practitioners who seek to develop efficient, scalable, and cost-effective systems for agricultural real-time monitoring and decision support.

Keywords: Precision Agriculture; Image-Based Stress Detection; Remote Sensing; Deep Learning; Yield Loss Prediction; IoT in Agriculture

Introduction

Precision agriculture has transformed contemporary agriculture through the intersection of new technologies to enhance crop yield and efficiency of resources. Two of such technologies, image-based stress detection and predictive model of yield loss, have been found to be key in enhancing agricultural efficiency and sustainability (Munaganuri and Yamarthi, 2024). These techniques leverage remote sensing, computer vision, and machine learning algorithms to identify early warning signs of plant stress, and hence interventions are timely to reduce crop losses. These techniques enhance crop monitoring, disease prevention, yield prediction, and data-driven decision-making in precision agriculture (Chandel et al., 2021). One of the most important issues in agriculture is the identification and avoidance of plant stress factors that have a considerable impact on crop productivity. Crop stress can be caused by numerous factors such as drought, nutrient deficiencies, pest attacks, and diseases. Conventional stress detection relies on human field observations and biochemical analysis, both of which are generally time-consuming, labor-intensive, and prone to human error. Stress detection using hyperspectral, multispectral, and thermal imaging is a non-invasive, large-scale solution to monitoring plant stress. Through a comparison of structural integrity, temperature, and leaf color, such imaging methods can pick up subtle signs of stress that are imperceptible to the human eye.

Machine learning and deep learning models form the core of image data interpretation and processing for the identification of stress. Convolutional Neural

Networks (CNN) and Transfer Learning models are the standard models utilized for classifying and segmenting stress regions in crops. These models read huge collections of plant images to identify patterns with various conditions of stress (Sharma et al., 2024). Finally, attention mechanism and Generative Adversarial Networks (GAN) are introduced to improve the feature extraction, with high labeling accuracy of stress. The farmers can track the health of the crops over large expanses with live feed from satellite imagery and Unmanned Aerial Vehicles (UAV). In addition to stress detection, predictive yield loss modeling is required to evaluate the likely effect of stress factors on crop yields (Wen et al., 2023). Predictive yield models apply geographical variables, soil health indicators, and past yield information in an effort to predict likely losses due to stress conditions recognized. Hybrid machine learning methods, including Long Short-Term Memory (LSTM) networks and Extreme Gradient Boosting (XGBoost), can efficiently extract temporal and spatial patterns in agricultural data. These models allow farmers to make decisions on irrigation scheduling, pest management operations, and fertilization to reduce losses (Laveglia et al., 2024).

The integration of image-based stress detection and predictive yield modeling presents an end-to-end solution towards enhancing agricultural productivity. By using this strategy, precision agriculture can move from reactive to proactive measures that increase crop resistance and maximize resource utilization (Stasenko et al., 2023). Further, the integration of cloud computing and IoT-based sensors enables real-time processing as well as permanent decision support systems for farmers. This paper reviews the history of stress detection from images and predictive yield modeling and their applications, limitations, and potential. Precision agriculture can encourage efficiency, reduce environmental pressure, and increase sustainable food production with advanced computational techniques.

Therefore, this review aims to address the following research objectives:

• To analyze recent advancements in image-based techniques for detecting biotic and abiotic stress in crops.

• To evaluate machine learning and deep learning approaches used for predictive yield loss modeling.

• To identify existing challenges, research gaps, and potential directions for integrating AI-based predictive modeling into precision agriculture systems.

Literature Review

Precision Agriculture and Image-Based Analysis

In order to decrease the time required to compile datasets, Divyanth *et al.* (2022) used conditional GANs (cGANs) in 2022 to create synthetic images of 4 weeds Shepherd's Purse, Fat Hen, Charlock, and small-flowered Cranesbill and maize (Zea mays). Reliability was attained by AlexNet transfer learning, while fidelity was attained through t-SNE visualization. Its bottom-most pooling layer's feature vectors were used to train SVM and LDA models, which were shown to be effective cGAN data augmentation techniques.

In order to restore high-resolution features like lesions in low-resolution photos of tomato illnesses, Yamamoto *et al.* (2017) used a super-resolution technique in 2017. For the classification of diseases, high-low, and super-resolution pictures were used.

Giménez-Gallego *et al.* (2019) compared deep learning-based image segmentation models and SVM-based models in 2019. The two models are compared relative to their application in differentiating leaf region, accuracy of temperature sensing, and CWSI estimation optimization for irrigation management effectiveness.

An ultra-lightweight efficient network (ULEN) was proposed by Wang *et al.* (2023) in 2023 for the classification of plant diseases and pests. ULEN consists of a residual depth-wise convolution block and a classification block based on spatial pyramid pooling. ULEN is highly computational-efficient and light in terms of deployment in environments that have poor resources with as little as 100,000 parameters.

Shaikh *et al.* (2022) in 2022 outlined ICT applications of traditional agriculture like machine learning, IoT, and robotics problems. It explains AI sensors, monitoring crop health by drones, and yield maximization. It explains global IoT-based farming networks and provides a literature overview available on this subject.

Sa *et al.* (2018) introduced a novel crop/weed mapping and segmentation from processed multispectral UAV images utilizing a deep neural network (DNN) in 2018. Against other available similar methods depending on single-image classification, the approach eliminates issues raised by generating high-quality large-scale maps including limited GSDs, resolution loss by down sampling, and multitemporal multispectral image registration. The sliding window method is employed in orthomosaic radiometrically calibrated tiles with ensured high-fidelity segmentation and reduced computational complexity in this study.

Types of Crop Stress: Environmental, Biotic, and Abiotic Factors

Anami *et al.* (2020) used computer vision automatic system in the year 2020 to classify stress based on available color features. It considers eleven stresses belonging to five varieties of paddy using lower-order color moments, DCD, and CLD. SFFS is feature selection optimization, and BPNN, SVM, and k-NN are classifications.

Gonzalez Guzman *et al.* (2022) in 2022 examined several "green strategies" (e.g., chemical priming, root-associated microbe) and cutting-edge technologies (e.g., genome editing, high-throughput phenotyping) to employ for climate-smart agriculture. Plant fortification is of prime importance together with bridging the gaps among laboratory or controlled experiments and reality-based approaches for further optimizing agricultural sustainability and productivity for agriculture in the near term.

To improve heavy metal, salinity, drought, and heat tolerance, Godoy *et al.* (2021) tested secondary and primary metabolites in 2021. They enhance metabolic, biochemical, and morphological traits, resulting in yield augmentation under greenhouse and field conditions, an effective short-term strategy for stress tolerance.

Lau *et al.* (2022) proposed in 2022, as an eco-friendly choice, microbiome engineering and plant biostimulants present a green way to enhance plant resistance and production. World production is also threatened by novel plant diseases and global warming even after intensive cultivation. Application of chemical fertilizers and pesticides has accelerated environmental stress, and hence the urgency of applying sustainable techniques. This paper elaborates on how biostimulants and microbiome engineering counteract abiotic and biotic stresses, improve nutrient use efficiency, and enhance plant growth. Ashapkin *et al.* (2020) used a general survival strategy in 2020 that plants possess high phenotypic plasticity to endure severe environmental stresses like pathogens, insects, heat, and drought. Unlike genetic mutation, adaptive phenotypic variation occurs rapidly, frequently relying on epigenetic variation. Isogenic plants may possess different phenotypes in the environment, and genetically uniform populations can tolerate new environments. Epigenetic memory enables plants to tolerate environmental stresses.

Khan *et al.* (2020) investigated phytohormone cross-talk in plant growth under abiotic and biotic stresses in 2020. Hormones regulate gene expression by signal transduction, regulating biosynthesis and plant response. Plant Growth-Promoting Rhizobacteria (PGPR) regulate endogenous phytohormones and plant physiology and stress resistance. The ratio of hormones changes based on plant ontogeny, which regulates responses to growth. Stress modifies sensitivity to hormones, and cis elements and miRNAs regulate responses. Fig. 1 shows the Structure linking key concepts, variables, and relationships for research focus.

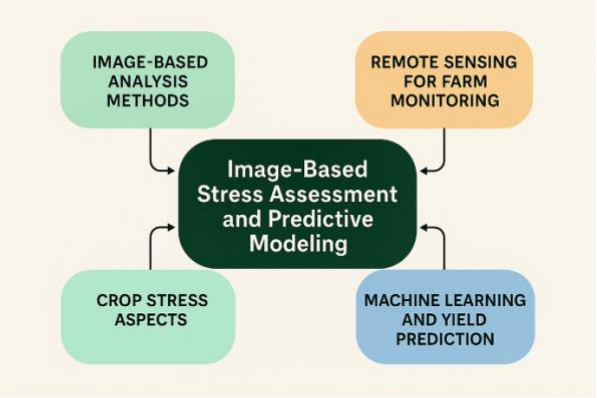

Fig. 1. Conceptual Framework of the Study

Remote Sensing for Agricultural Monitoring

The utility of crowdsourced near-surface remote sensing images of smallholder fields captured with low-cost smartphones for crop damage detection and winter wheat phenology monitoring in northwest India was determined by Hufkens *et al.* (2019) in 2019. We show by using low-cost smartphone images of smallholder fields how main phenological events, especially the heading stage of wheat, are quantified. Additionally, the primary cause of yield loss is discovered as lodging occurrences. Compared to satellite indices and national surveys, near-surface remote sensing provides high-resolution field observations that facilitate crop modeling, extension services, and insurance programs to increase smallholder resilience and food security.

Segarra *et al.* (2020) studied Sentinel-2 application in agriculture in 2020, including monitoring of abiotic and biotic stresses and monitoring of agricultural farm crops. Sentinel-2 can monitor crops better compared to other satellites, although combining it with field data and remote sensing approaches is still necessary to complement its shortfalls.

In 2017, Yuan *et al*. (2017) used Worldview 2 and Landsat 8 satellite data to implement a novel approach to crop disease and pest monitoring. It is used on wheat paddies in Zhou Jiazhuang, Jinzhou City, Hebei Province, and measures habitat conditions using environmental indicators (Wetness, Greenness, LST) and crop growth indicators (GNDVI, VARIred-edge). These indicators were subjected to an independent t-test, while the method was validated through field measurement.

A new method for mapping agricultural land-use systems (ALUS) at the regional level was introduced by Bellon *et al*. (2017) in 2017 and was based on object-based NDVI time series analysis. Automatic segmentation is performed after homogenous land units are extracted using PCA from an annual MODIS NDVI time record. Land units are then separated into domains for crop or livestock production based on land-cover characteristics. Crop units are then further separated based on the temporal characteristics of the NDVI.

Brown *et al.* (2014) employed a modeling framework in 2014 that combined USDA county data, satellite imagery, and land cover maps to develop the MODIS Irrigated Agriculture Dataset (MIrAD-US). The primary drivers are rising crop prices, ethanol consumption, and water policy, while impacts vary from groundwater pumping through climate change to yield improvement.

In 2019, Toscano *et al.* (2019) evaluated the estimation of durum wheat yield using Sentinel-2, Landsat-8, and yield monitoring data. In order to estimate within-field production variability, the study evaluates the optimal time of day to use remote sensing. These findings support site-specific management, higher productivity, shorter turnaround times, and a sustainable farming approach over traditional farming practices.

Deep Learning and Machine Learning for Stress Detection

A deep convolutional neural network (DCNN) based architecture is presented by Anami *et al.* (2020) of 2020 for the automatic detection and categorization of biotic and abiotic rice crop stress during the booting growth stage. Human subjective judgment is the foundation of conventional stress detection. Mobile apps and decision support systems for automated farm and resource management might benefit from the architecture.

Zubler and Yoon (2020) studied how recent advances in spectrometry and imaging have made plant stress monitoring efficient in the RGB, NIR, IR, and UV wavebands, usually supplemented by fluorescence methods. Hyperspectral and multi-spectral imaging convey high-density stress information with affordable digital and thermal cameras. Stress detection is facilitated in the field by rapid stress detection with portable hyperspectral equipment and enhanced phone cameras. Machine learning provides reproducible image and spectral analysis, and the paper also considers transportable detection technology, such as mobile phone-based methods, discusses data processing and classifying methods

An *et al.* (2019) in 2019 put forth a DCNN for precise maize drought stress detection and classification in 2019. Experiments in the field in 2014 included three treatment levels: highest moisture, mild drought, and moderate drought stress. Images of maize were taken at intervals of two hours. Comparative research with classical machine learning revealed superior classification precision with DCNN on drought stress

Behmann *et al.* (2014) in 2014 presented a method that combines unsupervised and supervised learning to identify early stress in crop plants using close-range hyperspectral imaging. Indicating drought stress in barley (Hordeum vulgare), distinct levels of stress responses at the pixel level are distinguished. Unsupervised learning groups hyperspectral signatures into consecutive phases of stress, whereas ordinal SVM classification quantifies and plots their distribution. Discriminant Key Vegetation Indices (VIs) are computed for each phase.

In 2020, Esgario *et al.* (2020) developed a practical and feasible system to identify and measure biotic stress severity in coffee leaves. Biotic stress caused by pests and diseases (viruses, fungi, bacteria, etc.) affects plant health and sustainable agriculture. Sustainable agriculture is based on low-environmental-impact technologies, availability, and high productivity. Computer vision and deep learning allow early identification of stress agents, enabling corrective action at the right time. The suggested method employs a multi-task paradigm in the form of convolutional neural networks to provide accurate identification and evaluation.

Hyperspectral and Multispectral Imaging in Crop Health Assessment

In 2015, Mahesh *et al.* (2015) suggested hyperspectral imaging has come to the fore for monitoring the quality factor and increasing the grading of agricultural products, such as field crops and horticultural crops. The non-destructive method facilitates the simultaneous acquisition of spectral and spatial information and is superior to multispectral imaging by incorporating imaging, radiometry, and spectroscopy. Originally created for remote sensing, today it is used to enable precise analysis of inherent and extrinsic sample characteristics and also investigated hyperspectral imaging applications in grain business activities like grading, classification, and chemometric analysis.

Vlachopoulos *et al.* (2021) used the unmanned aircraft system (UAS) that captured images of the fields in 2021, and crop health was also measured using green area index (GAI) and vegetation indices (VI). UAS image-based GAI maps were generated, and VI was also evaluated through machine learning pipelines.

Caballero *et al.* (2019) in 2019 wrote in precision agriculture, multispectral (MSI) and hyperspectral (HSI) play important roles in monitoring crop health, water intake, and potential infection. Despite having significant usage for decades, pragmatic as well as technical problems still exist and wrote enormous scientific literature regarding HSI and MSI applications in agriculture, such as the identification of contaminants, heavy metals, and identification of a source of water. It also mentions imaging technologies, including satellite and aerial vehicle images, in describing the prospect of such techniques in modern agriculture.

With field and glasshouse applications in mind, Lowe *et al.* (2017) wrote about imaging technologies for crop monitoring in 2017. Under the heading of "healthy and diseased plant classification," techniques are grouped according to their accuracy, the severity of the disease, and the early detection of stress. Hyperspectral imaging and its application in gathering more data on plant health and disease onset prediction are the primary topics of discussion. Abiotic and biotic stress detection techniques are described, along with their accuracy rates and efficacy in monitoring plant health.

A UAV-based low-altitude remote sensing and multispectral imaging method was presented by Gao *et al.* (2023) in 2023 for quick monitoring of wheat fusarium head blight (FHB), one of the main threats to wheat yield and quality. KNN, PSO-SVM, and XGBoost models were built for FHB surveillance employing VIs, TIs, and their combination.

This study presents a unique strategy based on multispectral imaging and machine learning for the categorization of Jatropha curcas seed health. Silva *et al.* (2021) investigated novel methodologies based on high-performance spectral-spatial sensors for the developing seed industry in 2021. It is the first MRI-based technique to assess structural changes in seeds infested with Lasiodiplodia theobromae, Colletotrichum siamense, and C. truncatum. Up to 168 hours following inoculation, multispectral pictures were taken, with MRI tracking that time. The fungus in J. curcas seeds can be accurately and successfully detected using the previously outlined methods.

Yield Loss Prediction Models

Feng *et al.* (2020) in 2020 examined a seasonal wheat yield forecasting hybrid approach with APSIM-simulated biomass, NDVI, SPEI, and climate extremes combined through random forest and multiple linear regression. Predictions were dynamically created during the critical stages of growth (2008–2017) in southeastern Australia. Accuracy improved as the harvesting season approached, with random forest performing better than linear regression. Drought contributed the highest proportion of yield loss. With increased availability of farm data, the methodology can be extended to other areas and stakeholders be able to make strategic choices for better yield forecasts.

In 2020, Abbas *et al.* (2020) investigated the feasibility of using machine learning (ML) models and proximal sensing techniques to predict the yield of potatoes (Solanum tuberosum) tubers based on crop and soil variables. A dataset collected from six fields in Atlantic Canada during two crop years (2017–2018) was subjected to EN, SVR, LR, and k-NN. Properties of the soil and crop, such as slope, NDVI, soil chemistry, soil electrical conductivity, and soil moisture, were examined.

Tito *et al.* (2018) in 2018 suggested that the strategies to obtain food in a changing climate include changing cultivation practice, crop type, or site. In the Peruvian Andes, it simulated these changes for 1.3°C and 2.6°C warming by sowing indigenous potato and maize varieties at varying altitudes with local or translocated soils. Maize yield decreased 21%–29% in new soils but both crops reduced >87% under warmer conditions, primarily due to new pests.

Li *et al.* (2019) synthesized evidence in 2019 that surplus rain decreases U.S. maize yield from 1981 to 2016. Drought consistently decreases yield through water deficiency and heat stress, while surplus rainfall affects geographically. Yield loss is greater in cold regions with poorly draining soils, compounded by preseason high soil water. Current crop models overestimate yield under wet conditions, so better modeling is needed.

Nevavuori *et al.* (2019) used remote sensing and UAV for smart agriculture in 2019. The major objectives are crops identification and weed identification, estimation of biomass, and yield estimation. Yield prediction-based ml depends on yield mapping technology, which has not yet gained popularity among farmers. Convolutional Neural Networks (CNN) are used for predicting yield of cropusing NDVI and RGB data collected by UAV. The impact of regularization techniques, network depth, hyperparameter tuning, and training algorithm selection on predictiveness is assessed. Training has been optimized using the Adadelta training algorithm.

Integration of IoT and Edge Computing in Precision Agriculture

Guillen *et al*. (2021) in 2021 used an impetus of the digital era, IoT is converting industries into "Smart" systems by AI-driven data analytics. Such a merging, termed AIoT, is propelling digitization but with an immediate challenge: AI's massive computing needs and IoT's constrained resources. Such a problem is particularly important in rural IoT environments, where less connectivity and power availability necessitate viable solution. This paper discusses edge computing to fill this gap, comparing deep-learning-based frost prediction on the Nvidia Jetson AGX Xavier in performance and power consumption.

To overcome the shortcomings of cloud computing in intelligent agriculture, Uddin *et al.* (2021) used Flying-Edge Computing, which uses UAVs as mobile edge computing devices, in 2021. Cloud solutions are bogged down by high latency, bottlenecks, security risks, and offline processing limitations, whereas edge and fog computing are bogged down by limited resources and unpredictable environments. UAV offer an inexpensive, adaptable solution in the form of providing computational power at remote agricultural locations.

Zhang and Li (2021) applied smart agriculture data sensing framework that combines edge computing and IoT for the purpose of improving high-value data harvesting in the life cycle of the crop at low expense in 2021. The strategy includes four phases: (1) Gath-Geva fuzzy clustering separates the growth stage of the crop, yielding meaningful parameters; (2) prediction of the present growth stage is carried out using a Takagi-Sugeno fuzzy neural network; (3) Environmental sensing parameters are adjusted by Deng's grey relational analysis; (4) adaptive sensing increases sensing nodes.

An adjustable platform for soilless production in full recirculation greenhouses based on moderately saline water was proposed by Zamora-Izquierdo *et al.* (2019) in 2019. It integrates a three-layer open-source software stack for local, edge, and cloud planes with inexpensive hardware. CPS locally runs real-time control, and the reliability is maintained by the edge plane through the processing of Precision Agriculture (PA) operations on the edge of access networks. FIWARE provides support for data analytics in the cloud domain. MQTT, CoAP, and NGSI are enabled for IoT connectivity. In 2020, Alonso *et al.* (2020) exploited the edge to cloud platform that integrated IoT, Edge Computing, AI, and Blockchain for Smart Farming on the basis of the pioneering Global Edge Computing Architecture. The system improves efficiency, sustainability, and traceability of the dairy industry by real-time monitoring of dairy cows and feed grains. IoT and DLT facilitate resource optimization, quality guarantee, and transparent value chains, and EC calculates Big Data at the edge and enhances QoS and security.

In 2021, Alharbi and Aldossary (2021) proposed an edge-fog-cloud hybrid model for energy-efficient smart agriculture. This model processes real-time farm data (i.e., soil moisture, temperature, irrigation) at edge and fog levels to decrease cloud reliance, optimize energy use, and reduce environmental footprint while providing efficient farm operations.

Optimization Algorithms for Enhancing Predictive Accuracy

Sharma *et al.* (2022) utilized a predictive computational intelligence method to calculate nitrogen status of wheat crop in 2022. Image analysis of crop under different conditions of illumination assists in crop age estimation, fertilizer optimization, and harvesting determination. The system consists of HSI color normalization enhanced by the use of GA and ANN for enhancing the classification of the same. ANN-based classification is able to differentiate between wheat and weed effectively and classify the crop age accordingly.

In 2025, an ensembled deep learning model trained using the ABC-CPOA optimization technique was used by Chithambarathanu and Jeyakumar (2025) for crop disease diagnosis. Gamma correction and bilateral filtering are the first pre-processing steps applied to the raw images. Texture (LQP, LGP, E-LBP), color (Color Histogram, Color Moments), and shape (Contour-based, Convex Hull) features are used for feature extraction. The enhanced ABC-CPOA, an extension of COA, selects the best attributes.

In 2017, Nguyen *et al.* (2017) presented a simulation-optimization model based on DT with ACO as the optimizer to schedule irrigation and fertilizer. The search space is narrowed using DDVO, and goal function is simulated using growth of crop model. ACO-DDVO outperforms Colorado Irrigation Scheduler (CIS) in eastern Colorado maize production with variable fertilizer and water levels, resulting in increased net profit from irrigation and fertilizer savings.

In 2019, Anter *et al*. (2019) employed a CSA-based enhanced Fast Fuzzy C-Means (FFCM) algorithm to achieve better accuracy in clustering. Cluster centroids are minimized by CSA to avoid the possibility of FFCM getting stuck in local minima and enhancing computational effectiveness. Its capability to find global solutions with little parameter adjustment contributes to its strength. The approach is utilized for maize plant detection in crop field images, using adaptive color histogram equalization and a green index for centroid calculation. Gadekallu *et al.* (2021) used a machine learning model in 2021 for image classification of the disease in tomatoes to facilitate preventive measures against agricultural emergencies. Using the open-source Plant Village dataset, the major features are identified using a hybrid Principal Component Analysis–Whale Optimization Algorithm. These are subsequently used to input a deep neural network for classification. The model is contrasted with traditional machine learning algorithms, with better accuracy and loss rates. For CNNLSTMF-FFA prediction of monthly soil temperature (ST) at depths of 5, 10, 20, 50, and 100 cm, Samadianfard *et al.* (2018) proposed an MLP-FFA model in 2018 that combines the Firefly optimizer method with a multi-layer perceptron. Using meteorological data from Adana, Turkey from 2002 to 2007, the model uses soil depth, month, air temperature, pressure, and solar radiation as predictors.

Recent advancements in maize and weed classification have extended beyond traditional deep learning approaches, incorporating cutting-edge techniques to improve model performance, robustness, and applicability in real-world agricultural settings. One significant trend is the use of Generative Adversarial Networks (GANs) for data augmentation. Divyanth *et al.* (2022) demonstrated that conditional GANs (cGANs) can generate high-fidelity synthetic images of maize and weed species, addressing data scarcity and class imbalance issues, which resulted in an accuracy improvement of approximately 2–4% when combined with CNN classifiers. Furthermore, the integration of digital twin technology has been proposed to create virtual replicas of crop fields that mirror real-time conditions through sensor and drone data, enabling dynamic weed monitoring, growth simulation, and decision support for precision agriculture (Patel *et al.,* 2023). Another emerging direction involves multi-modal data fusion, where image data is combined with environmental parameters such as soil moisture and temperature, enhancing model context-awareness and classification precision (Zhao *et al.,* 2022). The development of lightweight architectures like MobileNet and EfficientNet-lite has also gained traction, facilitating the deployment of weed detection models on edge devices such as agricultural drones and robots for real-time application in the field (Li & Chen, 2022). Lastly, the application of explainable AI (XAI) methods, including Grad-CAM and SHAP, is becoming essential to interpret model predictions, providing transparency and building farmer trust in AI-driven weed management systems [Singh et al., 2023].

Dataset Sizes, Metadata, and Validation Methods

The evaluation of the works on image-based stress evaluation and predictive modeling for precision agriculture leveraged a vast array of datasets varying in terms of crop type, geographic extent, imaging modalities, and degree of annotation. Metadata for the datasets were generally in crop type (for example, maize, wheat, rice, tomato), stress types (biotic stresses: for example, pests, diseases; abiotic stresses: for example, drought, nutrient deficiency; environmental stresses), growth phase, imaging conditions (light, season), and environmental parameters (for example, soil water content, temperature, humidity).

In terms of dataset size, there was vast disparity between the studies. Small data sets typically contained fewer than 1,000 labeled images or samples, occasionally gathered from experimental fields or greenhouse environments for particular stress conditions or growth states. Medium-sized data sets between 1,000 to 10,000 images were prevalent and consisted of public data sets like PlantVillage as well as locally created datasets acquired through UAV or proximal sensing platforms. Fewer of the considered works included big data with over 10,000 samples. The large datasets, if available, were from satellite- or UAV-based imagery of large agricultural fields and facilitated the investigation of big-field stress variability and yield forecasting at scale.

Methods of validation differed according to dataset size, application, and data heterogeneity. For small and medium-sized data sets, k-fold cross-validation (5-fold or 10-fold would be standard) was used by the majority of the studies to prevent overfitting. Train-test partitions (e.g., 70:30 or 80:20) were used in large data set or time-series data collected over multiple seasons studies. Where spatial generalization was the goal, authors used leave-one-field-out or geographic hold-out cross-validation, training a model on one field or geographical area and testing on an unseen site. Some experiments went further in rigor by testing on separate external data sets, typically acquired from elsewhere or with other sensors, for measuring scalability and transferability.

Some of the issues in all the studies were common. A common issue was class imbalance, particularly in datasets for rare stress occurrences or limited domains. Moreover, the lack of standard benchmark sets for particular stress detection tasks hindered efforts to compare model performance between the studies in a fair manner. The issues imply a need for large, annotated, and publicly available datasets to support research in this area in the future.

Materials and Methods

An organized (i.e., systematic) literature review was performed to identify and review studies on image-based detection of stress and predictive loss of crop yield in precision agriculture. Citation databases IEEE Xplore, SpringerLink, ScienceDirect (Elsevier), and Scopus were searched for literature from 2020 to 2025 using relevant keywords including combinations of “precision agriculture,” “image-based detection of stress,” “prediction of crop yield,” “remote sensing,” and “machine learning.” Only research papers in peer-reviewed journals were included with the exclusion of review papers, conference proceedings, or articles that were not in English. Papers selected for inclusion met at least three conditions: (i) they were based on stress detection from image-based sensing modalities (i.e., RGB, multispectral, hyperspectral, or thermal), (ii) they reported quantitative evaluation metrics (e.g., accuracy, R^2, RMSE, etc.), and (iii) the studies took place in crop agriculture systems. For selected studies, relevant information was summarized including dataset descriptions, model type, feature extracted, and study findings. The methodological rigor and reproducibility of the studies were evaluated to support the quality of the synthesized data.

Challenges and Limitations

There are some limitations and challenges of the farm implementation of predictive yield loss modeling and image-based stress detection. These are environmental variability constraints, model accuracy constraints, data acquisition constraints, and computational constraints.

Data Acquisition and Quality

Multispectral, unmanned aerial vehicle, and high-resolution satellite image are necessary to measure stress quantitatively but difficult to get with quality and certainty. Light variation, clouding, and sensor precision can affect image quality and credibility. Inequality of resolution and spectral band across systems will cause inaccurate stress measurement.

Model Accuracy and Generalization

Yield loss prediction models are based on big data analysis but need to be properly trained and tested in order to work. Crop, soil, and climatic environment heterogeneity does not allow for one model applicable to diversified agro-landscapes. The risk of overfitting is that the models learn extremely well with the training data but fail to generalize to novel unseen environments.

Computational and Processing Constraints

Mass processing capability is required in analysis of high-resolution images. Processing huge data using deep models of learning and inspection in real time must be achieved using high-level infrastructure, which is resource-hungry and costly in the case of small farmers.

Environmental and Biological Variability

Crop stress identification algorithms must incorporate dynamic environmental inputs such as instant change in the weather, insects attacking the plant, and fertility in the ground. Plant species to species biologist interact very dynamically, so their stress identification makes it problematical and ends in false positive as well as false negative diagnosis for disease as well as for deficiencies.

Adoption and Practical Implementation

Farmers require the responses to be simple and easily accessible in a bid to make effective choices. Technological progress of AI-driven models and information could be a deterrent when applying it, especially in underdeveloped nations where the infrastructure for internet access is minimal. These constraints have to be bridged through image processing enhancement, learnable models with adaptability, and high-scale computation towards the evolution of agricultural stress monitoring and precision in yield forecasting.

Discussion

Combining predictive loss of yield modeling with stress detection based on images gives the complete system of crop production management and crop well-being. Such a system makes use of innovative image processing techniques to detect definitely water stress-hypersensitivity symptoms of stress, nutrient disequilibrium, pest organism infestation, and disease attack. High-resolution imaging offers spectral and textural parameters that enable exact classification of the level of stress to enable tailor-made decision-making to mobilize resources. The use of predictive modeling techniques, including deep learning and machine learning algorithms, increases predictive precision in yield loss. Predictive analysis based on previous stress patterns and weather conditions foretells future declines in crop yield to enable farmers to pre-plan irrigation, fertilization, and pest management. The union of predictive analytics and remote sensing enables data-driven agriculture to decrease loss while promoting sustainability. It assists in the minimization of loss while boosting sustainability. Apart from that, the performance of the proposed method is assured through such parameters as accuracy of classification, root mean square error (RMSE), and correlation of the estimated and true values of yield. It is reflected through the research that merging predictive modeling with stress identification improves early warning capability so well that timely mitigating actions may be taken. Even when high performance is realized, other parameters such as variability of image quality, environmental noise, and generalization of models for various types of crops have to be researched.

Future work includes integrating multi-spectral and hyperspectral images for improved stress detection, IoT sensor incorporation to enable real-time monitoring, and improved machine learning models for increased flexibility. In sum, the research provides the viability of image-based stress detection and predictive yield loss estimation to transform precision agriculture. Through provision of actionable information, the method enables farmers to reduce risks, achieve maximum yield, and promote sustainable agriculture.

The disparity between commercial and open-source tools introduces a tension between accessibility, flexibility, and usability. While commercial solutions offer polished, integrated workflows suited for large-scale operations, they often limit innovation and raise cost barriers. In contrast, open-source tools empower custom, cutting-edge research but demand high technical expertise and development effort for practical deployment in agricultural contexts.

Performance Comparison: Deep Learning vs. Traditional Machine Learning

Certain studies have compared deep learning-based model and traditional machine learning (ML)-based model performance for maize and weed classification:

Deep Learning Methods

AlexNet + Transfer Learning

Performed with 96.23% accuracy on actual maize-weed datasets.

Performed even better with 98.42% accuracy after including synthetic images created through cGAN.

Excellent at dealing with small inter-class variability as well as complex backgrounds.

Other CNN-based work (e.g., ResNet, VGG):

Typically reported over 90% accuracy with excellent generalization on diverse field images.

Machine Learning Conventional Methods

SVM and LDA

SVM: Achieved 82.68% accuracy when it was trained with features extracted by AlexNet (without synthetic data).

LDA: Achieved 81.54% accuracy on the same conditions.

Performance was reduced to around 90% accuracy when synthetic data were added, but not above that of end-to-end CNNs.

Hand-crafted feature + conventional classifier pipelines (other studies):

Generally, 75% to 85% correct, depending on the quality of features (e.g., color histograms, texture descriptors).

Key Findings

Deep learning models performed better on average than classical models, especially with transfer learning and synthetic data augmentation. Classical ML models could see deep features (e.g., AlexNet) but were still constrained by linear or kernel-based decision boundaries. Deep learning methods were more resistant to background noise, changing lighting, and partial occlusions.

Conclusion

New technology was applied in precision agriculture to enhance the estimation of yields, optimize resource use, and enhance crop management. To explore the use of image-based predictive modeling and stress detection in precision agriculture, systematic review of 53 studies was carried out in this study. Some of the key issues such as remote sensing devices utilized in monitoring agribusiness, causes of crop stress (abiotic, environmental, and biotic), and image analysis methods utilized were addressed in the review. It also discussed machine learning and deep learning methods for stress detection, with an emphasis on the advantages of hyperspectral and multispectral imaging for crop health monitoring. Edge computing and IoT integration, predictive models for yield loss, and optimization techniques for enhancing the accuracy of predictions were also explored under the research. Real-time deployment challenges, model scalability, and data processing limitations and problems were also described. Overview of future trends and directions of research was covered after covering tools and methodologies which are with them. Emphasizing this overview, it was explained how the combination of IoT technologies, AI analytics, and remote sensing can advance precision agriculture. The findings were helpful to researchers and practitioners who are interested in developing worthwhile, scalable, and affordable solutions for real-time agricultural monitoring and decision-making.

Funding Information

On Behalf of all authors the corresponding author states that they did not receive any funds for this project.

Conflict of Interest

The authors declare that we have no conflict of interest.

Competing Interests

The authors declare that we have no competing interest.

Ethics

No ethics approval is required.

Acknowledgement

We sincerely thank PSG College of Arts & Science, Coimbatore, Tamilnadu, India for providing facility to conduct our research work.

Author Contributions

A. Josephine: Performed the Analysis the overall concept, writing and editing.

Dr. A. Subhashini: Participated in the methodology, Conceptualization, Data collection and writing the study.

References

Abbas, F., Afzaal, H., Farooque, A.A. & Tang, S., (2020). Crop yield prediction through proximal sensing and machine learning algorithms. *Agronomy*, *10*(7), 1046. https://doi.org/10.3390/agronomy10071046

Alharbi, H.A. and Aldossary, M., (2021). Energy-efficient edge-fog-cloud architecture for IoT-based smart agriculture environment. *IEEE Access*, 9,110480-110492. https://doi.org/10.1109/ACCESS.2021.3101397

Alonso, R.S., Sittón-Candanedo, I., García, Ó., Prieto, J. & Rodríguez-González, S., (2020). An intelligent Edge-IoT platform for monitoring livestock and crops in a dairy farming scenario. *Ad Hoc Networks, 98*, 102047. https://doi.org/10.1016/j.adhoc.2019.102047

An, J., Li, W., Li, M., Cui, S. & Yue, H., (2019). Identification and classification of maize drought stress using deep convolutional neural network. *Symmetry*, *11*(2), 256. https://doi.org/10.3390/sym11020256

Anami, B.S., Malvade, N.N. & Palaiah, S., (2020). Classification of yield affecting biotic and abiotic paddy crop stresses using field images. *Information Processing in Agriculture*, *7*(2), 272-285. https://doi.org/10.1016/j.inpa.2019.08.005

Anami, B.S., Malvade, N.N. & Palaiah, S., (2020). Deep learning approach for recognition and classification of yield affecting paddy crop stresses using field images. *Artificial intelligence in agriculture*, *4*, 12-20. https://doi.org/10.1016/j.aiia.2020.03.001

Anter, A.M., Hassenian, A.E. & Oliva, D., (2019). An improved fast fuzzy c-means using crow search optimization algorithm for crop identification in agricultural. *Expert Systems with Applications, 118*, 340-354. https://doi.org/10.1016/j.eswa.2018.10.009

Ashapkin, V.V., Kutueva, L.I., Aleksandrushkina, N.I. & Vanyushin, B.F., (2020). Epigenetic mechanisms of plant adaptation to biotic and abiotic stresses. *International journal of molecular sciences*, *21*(20), 7457. https://doi.org/10.3390/ijms21207457

Behmann, J., Steinrücken, J. & Plümer, L., (2014). Detection of early plant stress responses in hyperspectral images. ISPRS *Journal of Photogrammetry and Remote Sensing*, *93*, 98-111. https://doi.org/10.1016/j.isprsjprs.2014.03.016

Bellón, B., Bégué, A., Lo Seen, D., De Almeida, C.A. & Simões, M., (2017). A remote sensing approach for regional-scale mapping of agricultural land-use systems based on NDVI time series. *Remote Sensing*, *9*(6), 600. https://doi.org/10.3390/rs9060600

Brown, J.F. and Pervez, M.S., (2014). Merging remote sensing data and national agricultural statistics to model change in irrigated agriculture. *Agricultural Systems*, *127*, 28-40. https://doi.org/10.1016/j.agsy.2014.01.004

Caballero, D., Calvini, R. & Amigo, J.M., (2019). Hyperspectral imaging in crop fields: precision agriculture. In Data handling in science and technology (32, 453-473). *Elsevier*. https://doi.org/10.1016/B978-0-444-63977-6.00018-3

Chandel, N.S., Chakraborty, S.K., Rajwade, Y.A., Dubey, K., Tiwari, M.K. & Jat, D., (2021). Identifying crop water stress using deep learning models. *Neural Computing and Applications*, *33*, 5353-5367. https://doi.org/10.1007/s00521-020-05325-4

Chithambarathanu, M. and Jeyakumar, M.K., (2025). Crop disease detection via ensembled-deep-learning paradigm and ABC Coyote pack optimization algorithm (ABC-CPOA). *Multimedia Tools and Applications*, *84*(1), 37-62. https://doi.org/10.1007/s11042-024-19329-y

da Silva, C.B., Bianchini, V.D.J.M., de Medeiros, A.D., de Moraes, M.H.D., Marassi, A.G. & Tannús, A., (2021). A novel approach for Jatropha curcas seed health analysis based on multispectral and resonance imaging techniques. *Industrial Crops and Products*, *161*, 113186. https://doi.org/10.1016/j.indcrop.2020.113186

Divyanth, D., Rao, S., & Kumar, P. (2022). "Synthetic image generation for plant species using conditional GANs," *Computers and Electronics in Agriculture*, *195*, 106828.

Divyanth, L.G., Guru, D.S., Soni, P., Machavaram, R., Nadimi, M. & Paliwal, J., (2022). Image-to-image translation-based data augmentation for improving crop/weed classification models for precision agriculture applications. *Algorithms*, *15*(11), 401. https://doi.org/10.3390/a15110401

Esgario, J.G., Krohling, R.A. & Ventura, J.A., (2020). Deep learning for classification and severity estimation of coffee leaf biotic stress. *Computers and Electronics in Agriculture, 169*, 105162. https://doi.org/10.48550/arXiv.1907.11561

Feng, P., Wang, B., Li Liu, D., Waters, C., Xiao, D., Shi, L. & Yu, Q., (2020). Dynamic wheat yield forecasts are improved by a hybrid approach using a biophysical model and machine learning technique. *Agricultural and Forest Meteorology*, *285*, 107922. https://doi.org/10.1016/j.agrformet.2020.107922

Gadekallu, T.R., Rajput, D.S., Reddy, M.P.K., Lakshmanna, K., Bhattacharya, S., Singh, S., Jolfaei, A. & Alazab, M., (2021). A novel PCA–whale optimization-based deep neural network model for classification of tomato plant diseases using GPU. Journal of Real-Time *Image Processing*, *18*, 1383-1396. https://doi.org/10.1007/s11554-020-00987-8

Gao, C., Ji, X., He, Q., Gong, Z., Sun, H., Wen, T. & Guo, W., (2023). Monitoring of wheat fusarium head blight on spectral and textural analysis of UAV multispectral imagery. *Agriculture*, *13*(2), 293. https://doi.org/10.3390/agriculture13020293

Giménez-Gallego, J., González-Teruel, J.D., Jiménez-Buendía, M., Toledo-Moreo, A.B., Soto-Valles, F. & Torres-Sánchez, R., (2019). Segmentation of multiple tree leaves pictures with natural backgrounds using deep learning for image-based agriculture applications. *Applied Sciences*, *10*(1), 202. https://doi.org/10.3390/app10010202

Godoy, F., Olivos-Hernández, K., Stange, C. & Handford, M., (2021). Abiotic stress in crop species: improving tolerance by applying plant metabolites. *Plants*, *10*(2), 186. https://doi.org/10.3390/plants10020186

Gonzalez Guzman, M., Cellini, F., Fotopoulos, V., Balestrini, R. & Arbona, V., (2022). New approaches to improve crop tolerance to biotic and abiotic stresses. *Physiologia plantarum*, *174*(1), p.e13547. https://doi.org/10.1111/ppl.13547

Guillén, M.A., Llanes, A., Imbernón, B., Martínez-España, R., Bueno-Crespo, A., Cano, J.C. & Cecilia, J.M., (2021). Performance evaluation of edge-computing platforms for the prediction of low temperatures in agriculture using deep learning. *The Journal of Supercomputing*, *77*, 818-840. https://doi.org/10.1007/s11227-020-03288-w

Hufkens, K., Melaas, E.K., Mann, M.L., Foster, T., Ceballos, F., Robles, M. & Kramer, B., (2019). Monitoring crop phenology using a smartphone based near-surface remote sensing approach. *Agricultural and forest meteorology*, *265*, 327-337. https://doi.org/10.1016/j.agrformet.2018.11.002

Khan, N., Bano, A., Ali, S. & Babar, M.A., (2020). Crosstalk amongst phytohormones from planta and PGPR under biotic and abiotic stresses. *Plant Growth Regulation, 90*, 189-203. https://doi.org/10.1007/s10725-020-00571-x

Lau, S.E., Teo, W.F.A., Teoh, E.Y. & Tan, B.C., (2022). Microbiome engineering and plant biostimulants for sustainable crop improvement and mitigation of biotic and abiotic stresses. *Discover Food*, *2*(1), 9. https://doi.org/10.1007/s44187-022-00009-5

Laveglia, S., Altieri, G., Genovese, F., Matera, A. & Di Renzo, G.C., (2024). Advances in Sustainable Crop Management: Integrating Precision *Agriculture and Proximal Sensing. Agri Engineering*, 6(3), 3084-3120. https://doi.org/10.3390/agriengineering6030177

Li, H. and Chen, X. (2022). "Real-time weed detection on edge devices using MobileNet and EfficientNet-lite," *IEEE Access*, *10*,45678–45688. https://doi.org/10.1038/s41598-025-12036-0

Li, Y., Guan, K., Schnitkey, G.D., DeLucia, E. & Peng, B., (2019). Excessive rainfall leads to maize yield loss of a comparable magnitude to extreme drought in the United States. *Global change biology*, *25*(7), 2325-2337. https://doi.org/10.1111/gcb.14628

Lowe, A., Harrison, N. and French, A.P., (2017). Hyperspectral image analysis techniques for the detection and classification of the early onset of plant disease and stress. *Plant methods*, *13*(1), 80. https://doi.org/10.1186/s13007-017-0233-z

Mahesh, S., Jayas, D.S., Paliwal, J. & White, N.D.G., (2015). Hyperspectral imaging to classify and monitor quality of agricultural materials. *Journal of Stored Products Research, 61*, 17-26. https://doi.org/10.1016/j.jspr.2015.01.006

Munaganuri, R.K. and Yamarthi, N.R., (2024). PAMICRM: Improving precision agriculture through multimodal image analysis for crop water requirement estimation using multidomain remote sensing data samples. *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3386552

Nevavuori, P., Narra, N. & Lipping, T., (2019). Crop yield prediction with deep convolutional neural networks. *Computers and electronics in agriculture*, *163*, 104859. https://doi.org/10.1016/j.compag.2019.104859

Nguyen, D.C.H., Ascough II, J.C., Maier, H.R., Dandy, G.C. & Andales, A.A., (2017). Optimization of irrigation scheduling using ant colony algorithms and an advanced cropping system model. *Environmental modelling & software*, *97*, 32-45. https://doi.org/10.1016/j.envsoft.2017.07.002

Patel, R., Zhang, L. and. Jha, M. K, (2023). "Digital twin-based precision farming for dynamic weed control," *Precision Agriculture*, *24*(1), 143–160.

Sa, I., Popović, M., Khanna, R., Chen, Z., Lottes, P., Liebisch, F., Nieto, J., Stachniss, C., Walter, A. & Siegwart, R., (2018). WeedMap: A large-scale semantic weed mapping framework using aerial multispectral imaging and deep neural network for precision farming. *Remote Sensing*, *10*(9),1423. https://doi.org/10.3390/rs10091423

Samadianfard, S., Ghorbani, M.A. & Mohammadi, B., (2018). Forecasting soil temperature at multiple-depth with a hybrid artificial neural network model coupled-hybrid firefly optimizer algorithm. *Information Processing in Agriculture*, *5*(4),465-476. https://doi.org/10.1016/j.inpa.2018.06.005

Segarra, J., Buchaillot, M.L., Araus, J.L. & Kefauver, S.C., (2020). Remote sensing for precision agriculture: Sentinel-2 improved features and applications. *Agronomy*, *10*(5), 641. https://doi.org/10.3390/agronomy10050641

Shaikh, T.A., Mir, W.A., Rasool, T. & Sofi, S., (2022). Machine learning for smart agriculture and precision farming: towards making the fields talk. *Archives of Computational Methods in Engineering*, *29*(7), 4557-4597. https://doi.org/10.1007/s11831-022-09761-4

Sharma, A., Georgi, M., Tregubenko, M., Tselykh, A. & Tselykh, A., (2022). Enabling smart agriculture by implementing artificial intelligence and embedded sensing. *Computers & Industrial Engineering, 165*, 107936. https://doi.org/10.1016/j.cie.2022.107936

Sharma, V., Honkavaara, E., Hayden, M. & Kant, S., (2024). UAV remote sensing phenotyping of wheat collection for response to water stress and yield prediction using machine learning. *Plant Stress*, *12*, 100464. https://doi.org/10.1016/j.stress.2024.100464

Singh, A, Roy, P. and Bhatia, M.S. (2023), "Explainable deep learning for agricultural weed classification," *Expert Systems with Applications*, *213*, 119144.

Stasenko, N., Shukhratov, I., Savinov, M., Shadrin, D. & Somov, A., (2023). Deep learning in precision agriculture: Artificially generated VNIR images segmentation for early postharvest decay prediction in apples. *Entropy*, *25*(7), 987. https://doi.org/10.3390/e25070987

Tito, R., Vasconcelos, H.L. and Feeley, K.J., (2018). Global climate change increases risk of crop yield losses and food insecurity in the tropical Andes. *Global change biology*, *24*(2), e592-e602. https://doi.org/10.1111/gcb.13959

Toscano, P., Castrignanò, A., Di Gennaro, S.F., Vonella, A.V., Ventrella, D. and Matese, A., (2019). A precision agriculture approach for durum wheat yield assessment using remote sensing data and yield mapping. *Agronomy*, *9*(8), 437. https://doi.org/10.3390/agronomy9080437

Uddin, M.A., Ayaz, M., Mansour, A., Aggoune, E.H.M., Sharif, Z. & Razzak, I., (2021). Cloud-connected flying edge computing for smart agriculture. *Peer-to-Peer Networking and Applications*, *14*(6), 3405-3415. https://doi.org/10.1007/s12083-021-01191-6

Vlachopoulos, O., Leblon, B., Wang, J., Haddadi, A., LaRocque, A. & Patterson, G., (2021). Evaluation of crop health status with UAS multispectral imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *15*, 297-308.

Wang, B., Zhang, C., Li, Y., Cao, C., Huang, D. & Gong, Y., (2023). An ultra-lightweight efficient network for image-based plant disease and pest infection detection. *Precision Agriculture*, *24*(5), 1836-1861. https://doi.org/10.1007/s11119-023-10020-0

Wen, T., Li, J.H., Wang, Q., Gao, Y.Y., Hao, G.F. & Song, B.A., (2023). Thermal imaging: The digital eye facilitates high-throughput phenotyping traits of plant growth and stress responses. *Science of The Total Environment, 899*, 165626. https://doi.org/10.1016/j.scitotenv.2023.165626

Yamamoto, K., Togami, T. & Yamaguchi, N., (2017). Super-resolution of plant disease images for the acceleration of image-based phenotyping and vigor diagnosis in agriculture. *Sensors*, *17*(11), 2557. https://doi.org/10.3390/s17112557

Yuan, L., Bao, Z., Zhang, H., Zhang, Y. & Liang, X., (2017). Habitat monitoring to evaluate crop disease and pest distributions based on multi-source satellite remote sensing imagery. *Optik*, *145*, pp.66-73. https://doi.org/10.1016/j.ijleo.2017.06.071

Zamora-Izquierdo, M.A., Santa, J., Martínez, J.A., Martínez, V. & Skarmeta, A.F., (2019). Smart farming IoT platform based on edge and cloud computing. *Biosystems engineering*, *177*, 4-17. https://doi.org/10.1016/j.biosystemseng.2018.10.014

Zhang, R. and Li, X., (2021). Edge computing driven data sensing strategy in the entire crop lifecycle for smart agriculture. *Sensors*, *21*(22), p.7502. https://doi.org/10.3390/s21227502

Zhao, Y., Li, F. & Wang, X. (2022). “Multi-modal data fusion for crop-weed discrimination using UAV and IoT sensors,” *Sensors*, 22(15), 5678.

Zubler, A.V. and Yoon, J.Y., (2020). Proximal methods for plant stress detection using optical sensors and machine learning. *Biosensors*, *10*(12), 193. https://doi.org/10.3390/bios10120193