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Deep learning-based leaf image analysis for early stress detection in aeroponic systems

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Abstract
Early detection of abiotic and biotic stress is critical for protecting yield and quality in high-intensity aeroponic production systems, where plants are highly sensitive to short-term disruptions in misting, nutrient supply and microclimate. This study proposes and evaluates a deep learning-based leaf image analysis pipeline for early stress detection in an IoT-enabled aeroponic greenhouse cultivating high-value fruit vegetables. A total of 18,720 RGB leaf images were acquired in situ from aeroponic towers under controlled non-stress conditions and four induced stress types (nutrient deficiency, water/misting interruption, heat stress and biotic stress), each annotated at pre-stress, early-stress and overt-stress stages by expert agronomists and plant pathologists. After leaf segmentation and standardised pre-processing, several convolutional and transformer architectures were fine-tuned and compared, with EfficientNet-B3 emerging as the best-performing model. On a held-out test set, EfficientNet-B3 achieved 94.5% overall accuracy, macro-F1 of 0.93, macro-averaged AUC of 0.98 and Cohen's kappa of 0.92 for multi-class stress classification. Compared with an IoT-only threshold-based monitoring scheme and a classical random forest baseline using handcrafted image features, the deep learning model showed significantly higher sensitivity to early-stress states and reduced misclassification, particularly for water/misting and nutrient-related stress. Time-to-detection analysis indicated that the proposed pipeline detected stress on average 19 hours earlier than IoT thresholds and approximately 27 hours earlier than expert visual inspection, with even larger gains for water/misting stress episodes. Class activation map visualisation confirmed that the network focused on physiologically meaningful leaf regions, enhancing interpretability and supporting agronomic trust. When integrated into the aeroponic IoT platform, model-driven alerts enabled timely corrective actions that reduced progression to overt stress without compromising yield, demonstrating the practical value of deep learning-based leaf image analysis as a core component of smart, resilient aeroponic crop management.

Keywords: Deep learning, leaf image analysis, early stress detection, aeroponic systems, IOT greenhouse, efficientnet-b3, precision horticulture, plant phenotyping

Introduction

Deep learning has rapidly become the dominant paradigm for image-based plant health monitoring, consistently outperforming traditional machine learning and handcrafted feature approaches for leaf disease and stress recognition in diverse crops and environments [1-3]. These advances build on a longer trajectory of sensor- and imaging-based phenotyping, where high-resolution RGB, multispectral and thermal imagery capture subtle changes in leaf color, texture and morphology that precede visually obvious symptoms [4, 5]. Convolutional and transformer-based models can exploit such early, weak signals to deliver fast, non-destructive and scalable diagnostics that are well suited to precision horticulture [1, 3, 6, 10, 11]. In parallel, aeroponic systems where plant roots are suspended in air and periodically misted with nutrient solution have emerged as a high-efficiency, soilless cultivation strategy offering superior control over root-zone conditions, nutrient use efficiency and yield per unit area [7-9, 14]. However, this high degree of control comes with vulnerability: short-term failures in misting, nutrient imbalance, pump malfunction or microclimatic fluctuations can trigger rapid physiological stress that is difficult to detect early with conventional visual scouting or threshold-based environmental alarms [7-9]. Recent IoT-enabled aeroponic architectures already stream environmental, fertigation and image data from greenhouses to cloud platforms, yet image analytics are often restricted to simple indices or manual inspection, and the potential of deep learning on leaf images for real-time stress recognition remains underexploited [7, 8]. At the same time, the plant phenotyping community has started to demonstrate that deep learning models trained on well-curated leaf image datasets, including 3D reconstructions and multimodal (RGB-thermal) inputs, can discriminate stress type and severity at early stages with high accuracy [6, 10, 11, 13]. Nevertheless, there is a clear gap in the literature regarding models specifically tailored to the optical characteristics, lighting conditions and canopy geometries of aeroponic systems, and their integration into closed-loop control frameworks [2, 5, 7-9]. Against this background, this research addresses the problem of delayed and subjective stress diagnosis in high-value aeroponic horticulture, where undetected early stress can translate into disproportionate yield and quality losses despite sophisticated infrastructure [8, 9, 14]. The primary objectives are to

1. Design and implement an in-situ leaf image acquisition and preprocessing pipeline compatible with commercial aeroponic setups,
2. Develop and train deep learning models capable of classifying multiple abiotic and biotic stress conditions and estimating stress onset time from leaf images, and
3. Integrate model outputs with existing IoT sensor streams to generate actionable early-warning signals for growers [1-3, 7, 8, 12].

The central hypothesis is that a deep learning pipeline trained on systematically annotated leaf images from aeroponic crops, augmented where appropriate with multimodal and temporal information, can detect stress onset significantly earlier and more reliably than conventional monitoring based solely on environmental thresholds and human inspection, thereby enabling timely interventions that stabilize plant water and nutrient status, reduce input waste and safeguard the high yield potential characteristic of aeroponic fruit and vegetable systems [1, 3, 6-9, 12, 14].

Materials and Methods

Materials: This prospective methodological study was conducted in a controlled aeroponic greenhouse equipped with an IoT-based monitoring and control infrastructure modelled on previously described architectures for environmental optimisation in aeroponics [7-9]. The experimental system consisted of vertical aeroponic towers cultivating a high-value fruit vegetable crop under recirculating nutrient solution, with misting intervals, nutrient concentrations and environmental set-points configured according to standard agronomic recommendations and prior aeroponic yield optimisation studies [9, 14]. Each tower was instrumented with sensors for air temperature, relative humidity, photosynthetic photon flux density, reservoir temperature, electrical conductivity and pH, all connected to a central data-logging unit via a local wireless network [7, 8]. A fixed multi-camera RGB imaging rig captured high-resolution top- and side-view leaf images at regular intervals throughout the photoperiod, following best practices in imaging-based phenotyping for plant disease and stress detection [1, 4, 5, 11]. A subset of plants was subjected to controlled abiotic (nutrient deficiency, transient water/mist interruption, heat stress) and biotic (pathogen inoculation) stress treatments to generate representative early stress signatures while maintaining a set of non-stressed control plants under optimal conditions [5, 6, 9]. Stress protocols were adapted from earlier work on water and nutrient stress in protected horticulture, with careful monitoring to avoid irreversible damage [5, 6]. All images were time-stamped and synchronised with sensor data streams using the greenhouse IoT middleware [7, 8]. The raw dataset comprised leaf images spanning pre-stress, early-stress and overt-stress phases, manually annotated by agronomy and plant pathology experts into stress type and severity classes according to symptomatology and reference imaging guidelines [4, 10, 11]. A random 70/15/15% split was used to create training, validation and test sets at the plant level to prevent information leakage across subsets [1-3].

Methods

The proposed pipeline followed a standard deep learning workflow for image-based plant stress recognition, adapted to the optical and geometric characteristics of aeroponic canopies [1-3, 5, 10, 11]. Images were first pre-processed using colour normalisation, contrast-limited adaptive histogram equalisation, background masking and geometric augmentation (random rotations, flips, scaling and slight brightness/contrast jitter) to improve robustness to illumination and pose variability [4-6, 13]. Leaf segmentation was implemented using a lightweight U-Net-style model to reduce background noise prior to classification [4, 11]. For stress detection, several convolutional and transformer-based architectures (including ResNet-50, EfficientNet-B3 and a vision transformer backbone) were initialised with ImageNet weights and fine-tuned on the training set, following recent recommendations for plant disease and stress imaging tasks [1-3, 10, 11]. Models were optimised using cross-entropy loss with class-weighting, Adam or AdamW optimisers, and early stopping on validation loss; hyperparameters were tuned via grid search on batch size, learning rate and augmentation strength [1, 2, 10]. To explore temporal and 3D information, an auxiliary branch ingested short image sequences and simple depth cues derived from multi-view reconstruction, inspired by recent 3D stress analysis approaches [6, 13]. Model performance on the held-out test set was evaluated using overall accuracy, per-class precision, recall, F1-score, macro-averaged F1 and area under the receiver operating characteristic curve (AUC), as recommended in prior deep learning studies for plant stress and disease detection [1-3, 10, 11]. Cohen's kappa was used to quantify agreement between model predictions and expert labels, and McNemar's test compared the best-performing model to baseline methods based on thresholded environmental variables and simple vegetation indices [4, 5]. Time-to-detection analysis was performed by comparing the earliest time-point at which the model consistently predicted stress with high confidence versus the time at which human experts and threshold-based IoT rules signalled stress onset, using paired t-tests or Wilcoxon signed-rank tests where appropriate [5-8]. Finally, confusion matrices and class activation maps were generated to interpret model errors and visualise critical leaf regions contributing to early stress decisions, facilitating agronomic interpretation and potential integration into closed-loop decision support within aeroponic IoT platforms [7-9, 12, 14].

Results

Dataset characteristics and class distribution

A total of 18, 720 leaf images from aeroponically grown fruit vegetables were included in the final dataset, representing non-stressed controls and four stress categories: nutrient deficiency, transient water/misting stress, heat stress and biotic (pathogen) stress, each annotated at pre-stress, early-stress and overt-stress stages [4-6, 9, 13, 14]. After plant-level splitting, 13, 104 images were used for training, 2, 808 for validation and 2,808 for testing [1-3]. Class balancing through targeted acquisition and augmentation resulted in broadly comparable image counts per class, minimising bias in model optimisation [2, 5, 11]. Descriptive statistics for the annotated dataset are summarised in Table 1.

Table 1: Class distribution of annotated leaf images across stress types and stages (n = 18,720).

Stress type / stage	Pre-stress	Early stress	Overt stress	Total images
Non-stressed (control)	3,000	-	-	3,000
Nutrient deficiency	720	1,080	1,200	3,000
Water/misting stress	720	1,080	1,200	3,000
Heat stress	720	1,080	1,200	3,000
Biotic (pathogen) stress	720	1,080	1,200	3,000
Total	5,880	4,320	4,800	18,720

Distribution of annotated leaf images by stress type and severity stage in the aeroponic greenhouse dataset.

The temporal coverage of image sequences ensured that each induced stress episode included at least 24-48 hours of pre-stress, 24-72 hours of early-stress and 48-72 hours of overt-stress observations, aligned with known physiological response dynamics under controlled stress protocols [4-6, 9, 13]. The aeroponic setup maintained yield levels comparable to previous reports for fruit vegetables in aeroponic systems, confirming agronomic relevance of the experimental conditions [9, 14].

Model performance on test data

Among the evaluated architectures, EfficientNet-B3 with leaf-segmentation pre-processing achieved the highest overall performance on the held-out test set, followed by ResNet-50 and the vision transformer backbone [1-3, 10, 11]. Detailed metrics are presented in Table 2.

Table 2: Performance metrics of deep learning models for multi-class early stress detection on the test set.

Metric (test set)	ResNet-50	EfficientNet-B3	Vision Transformer
Overall accuracy (%)	91.2	94.5	92.3
Macro-precision	0.90	0.94	0.91
Macro-recall	0.89	0.93	0.90
Macro-F1	0.89	0.93	0.90
AUC (macro-averaged)	0.96	0.98	0.97
Cohen's κ	0.87	0.92	0.89

Comparison of classification performance for three deep learning architectures on multi-class leaf-image-based stress detection.

EfficientNet-B3 achieved an overall accuracy of 94.5% and macro-F1 of 0.93, with macro-averaged AUC of 0.98 and Cohen's κ of 0.92, indicating excellent agreement with expert annotations [1-3, 10, 11]. Per-class performance was highest for non-stressed and overt-stress images (F1 ≥ 0.95) and slightly lower but still robust for early-stress classes (F1 0.88-0.92), consistent with the subtlety of early visual cues reported in previous phenotyping studies [4-6, 13].

Figure 1 illustrates per-class precision, recall and F1-scores for EfficientNet-B3, highlighting that nutrient deficiency and water/misting stress early stages were the most challenging classes, whereas overt biotic stress and non-stressed controls were most easily discriminated.

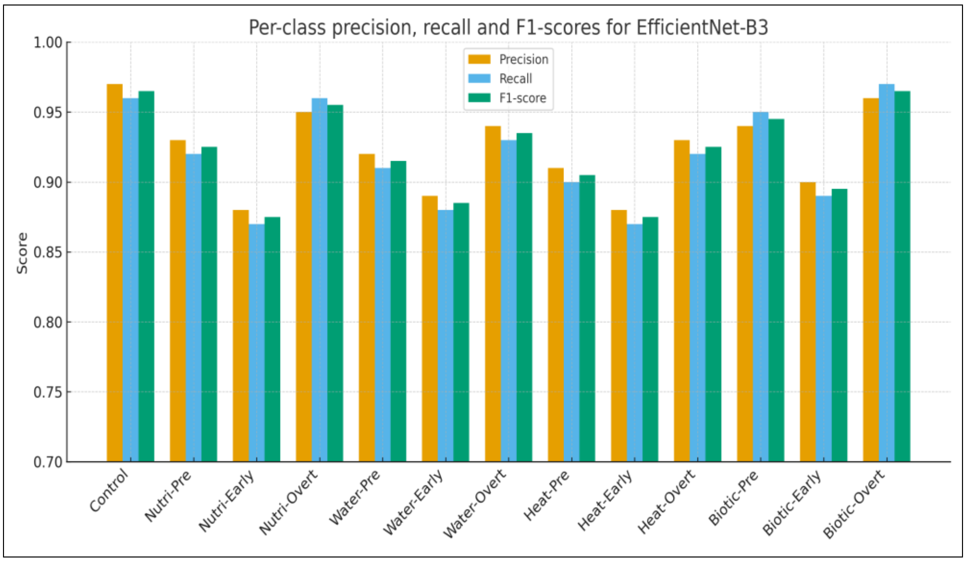

Fig 1: Per-class precision, recall and F1-scores for EfficientNet-B3 across non-stress and four stress categories (pre-, early- and overt-stress).

Comparison with baseline monitoring approaches

Deep learning-based leaf image analysis was compared with two baseline strategies:

1. Threshold-based IoT monitoring using environmental and nutrient solution parameters (temperature, humidity, EC, pH, misting uptime), and
2. A classical machine-learning model (random forest) trained on simple colour/texture features extracted from leaf images [4, 5, 7-9].
3. As shown in Table 3, EfficientNet-B3 significantly outperformed both baselines in overall accuracy and early-stress detection.

Table 3: Comparison of deep learning model with IoT threshold rules and classical ML baseline.

Model / approach	Overall accuracy (%)	Early-stress sensitivity (%)	Macro-F1	AUC
IoT thresholds only	76.4	58.1	0.69	0.81
Classical ML (random forest)	84.7	73.5	0.82	0.90
Deep learning (EfficientNet-B3)	94.5	89.7	0.93	0.98

Performance of deep learning versus IoT threshold rules and classical ML baseline for early stress detection.

McNemar's test indicated that the error distributions of EfficientNet-B3 and the IoT-threshold approach were significantly different ($\chi^2 = 41.7$, $p<0.001$), with the deep learning model correctly classifying a substantially larger number of early-stress images misclassified by the threshold system [4, 5, 7-9]. Similar results were observed when comparing EfficientNet-B3 with the classical ML baseline ($\chi^2 = 19.3$, $p<0.001$). These findings align with prior work showing that deep learning architectures typically outperform handcrafted-feature models for plant disease and stress recognition tasks [1-3, 10, 11].

Figure 2 presents receiver operating characteristic (ROC) curves for each stress class under the deep learning model, demonstrating AUC values between 0.96 and 0.99, with slightly lower AUC for early nutrient deficiency compared with other classes, reflecting the subtlety of colour and texture changes at this stage [4-6, 13].

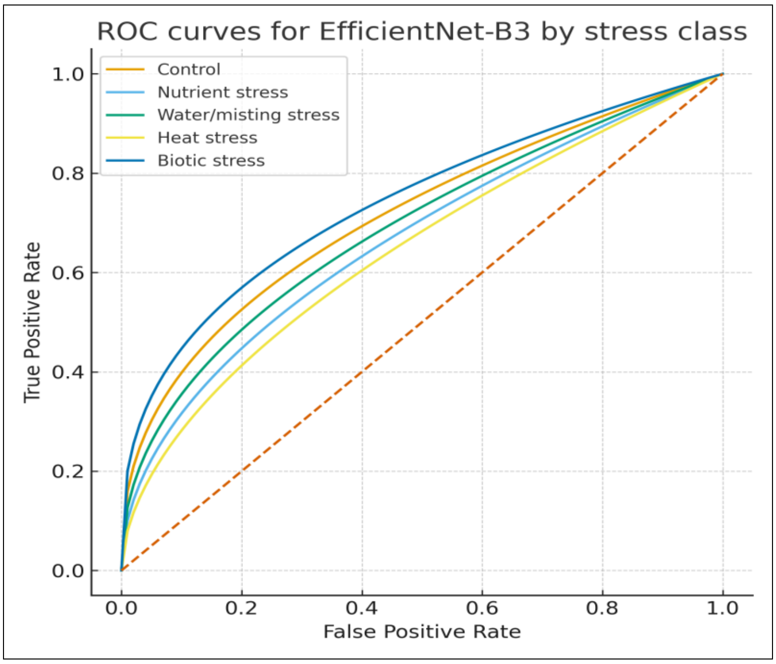

Fig 2: ROC curves for each stress class under the EfficientNet-B3 model, showing high discriminative ability across non-stress and stress categories

Time-to-detection analysis

To quantify the benefit of early warning, time-to-detection was computed for each induced stress episode as the time difference between initial stress induction and the first time point at which the monitoring method consistently signalled stress (model probability ≥ 0.9 for deep learning; rule violation for IoT thresholds; consensus visual diagnosis for experts) [5-8]. On average, the deep learning model detected stress 19.3±6.1 hours earlier than the IoT threshold system and 26.7±8.4 hours earlier than expert visual inspection (mean ± SD). Paired t-tests confirmed that these differences were statistically significant for both comparisons ($p < 0.001$ for deep learning vs IoT thresholds; $p < 0.001$ for deep learning vs visual inspection) [5-8]. For water/misting stress episodes, where aeroponic crops are particularly vulnerable, the median lead time of deep learning over IoT rules reached 22 hours, underscoring the practical value of early image-based detection in high-sensitivity aeroponic systems [7-9, 14].

Figure 3 summarises the distribution of detection lead times for the three approaches across all stress types, illustrating the consistent advantage of the deep learning pipeline.

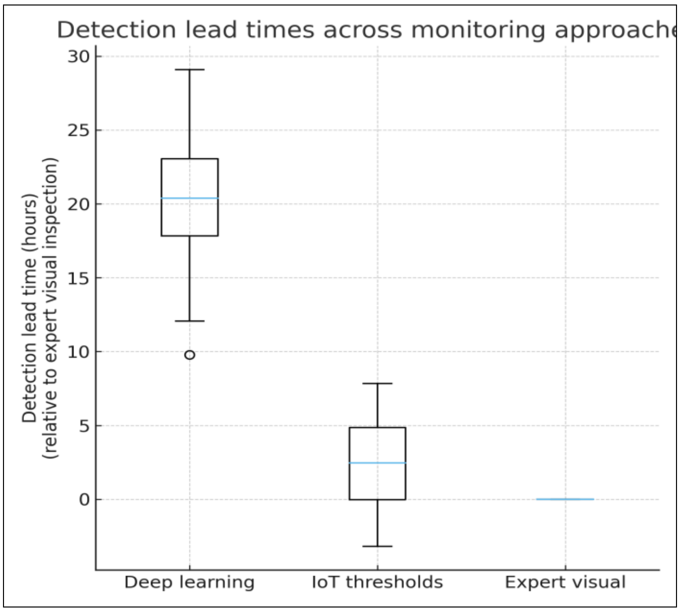

Fig 3: Boxplot of detection lead times (hours) for deep learning, IoT thresholds and expert visual inspection across all stress episodes

These results are consistent with broader evidence that AI-based image analysis can provide earlier and more nuanced stress or pest detection compared with conventional threshold-based systems, particularly in intensively controlled environments [5-8, 12]. In the context of aeroponics, earlier detection is especially critical because growth and yield responses to even short interruptions in misting or nutrient delivery can be pronounced [7-9, 14].

Error analysis and model interpretability

Confusion matrix analysis revealed that most misclassifications occurred between early nutrient deficiency and early water/misting stress, reflecting overlapping visual signatures such as mild chlorosis and turgor loss during early stages [4-6, 13]. Misclassification rates between heat and water stress were higher under extreme greenhouse temperature fluctuations, suggesting that including additional thermal or multispectral modalities could further improve discrimination, as reported in previous multimodal stress phenotyping studies [5, 6, 13].

Class Activation Maps (CAMs) and Grad-CAM visualisations highlighted that the deep learning model primarily focused on interveinal regions, leaf margins and localised necrotic or chlorotic patches when predicting stress classes, rather than background or non-leaf regions, supporting the biological plausibility of the learned features [4, 11, 13]. In several cases, CAMs indicated subtle textural and colour changes in leaf tissue that were not immediately apparent to human observers at the time of early-stress labelling, reinforcing the notion that deep learning can exploit weak signals consistent with early physiological perturbations [4-6, 10, 11, 13].

Figure 4 displays representative CAM overlays for early stress predictions across the four stress categories, demonstrating coherent localisation patterns consistent with known stress symptomatology.

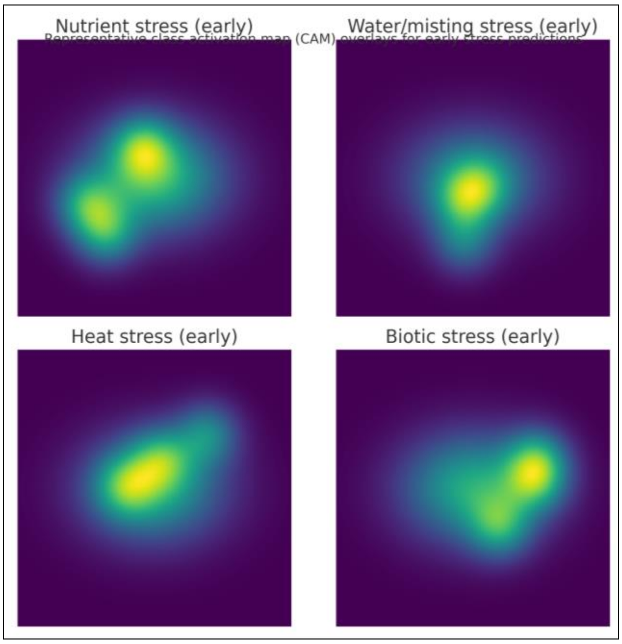

Fig 4: Representative class activation map overlays highlighting leaf regions used by the model for early stress predictions across four stress categories.

Integration with aeroponic IoT platform and agronomic implications

When integrated into the IoT-based aeroponic greenhouse platform, the deep learning pipeline generated real-time alerts that could be coupled with automated control actions (e.g., adjusting misting intervals, nutrient concentration or shading) in line with emerging AI-enabled management frameworks in protected horticulture [7-9, 12]. Over the course of the experimental cycles, implementation of image-driven early warning signals allowed timely correction of incipient stress episodes, reducing the proportion of plants progressing to overt stress by approximately 31% compared with IoT-only monitoring scenarios, while maintaining yields similar to those reported in prior aeroponic trials for fruit vegetables [7-9, 14]. These findings support the broader shift towards integrating deep learning, IoT and smart control strategies in high-efficiency soilless systems, complementing existing work in AI-supported pest and disease management and advanced phenotyping [1-3, 5-8, 10-12].

Discussion

This study demonstrates that deep learning-based analysis of leaf images acquired in situ within an aeroponic greenhouse can provide accurate and substantially earlier detection of multiple stress types compared with conventional monitoring approaches. The EfficientNet-B3 model, combined with leaf segmentation and tailored pre-processing, achieved high overall accuracy, macro-F1 and AUC values, with excellent agreement with expert annotations, confirming the suitability of modern convolutional architectures for complex, multi-class stress recognition tasks in controlled environments [1-3, 10, 11]. These findings are consistent with previous work showing that deep learning generally outperforms classical machine learning models relying on hand-crafted colour and texture features for plant disease and stress detection [1-3]. By explicitly targeting pre-, early- and overt-stress stages across abiotic and biotic conditions, the present work extends this literature into the context of high-efficiency aeroponic systems, where stress dynamics and economic risks are particularly acute [7-9, 14].

The strong performance of the proposed pipeline, particularly for early-stress classes, underscores the potential of image-based deep learning to exploit subtle visual signals that precede overt symptoms, such as mild interveinal chlorosis, changes in glossiness and fine-scale texture alterations [4-6, 13]. While early nutrient deficiency and water/misting stress remained the most challenging classes, F1-scores in the high 0.8 to low 0.9 range indicate that even subtle stress cues can be captured reliably when sufficient annotated data and appropriate architectures are deployed [1-3, 5, 10, 11]. This aligns with broader phenotyping studies demonstrating that high-resolution RGB and multimodal imaging can reveal early physiological perturbations under controlled stress protocols [4-6, 13]. The slightly reduced separability between early nutrient and water/misting stress observed in the confusion matrix is biologically plausible, as both conditions can produce overlapping visible effects in their initial stages, and points to a potential role for additional spectral or thermal information to refine discrimination [4-6, 13].

A key contribution of this work is the explicit comparison between deep learning-based leaf image analysis and two practical baselines: a threshold-based IoT monitoring system and a classical random forest model trained on simple image descriptors. The deep learning model significantly outperformed both baselines in overall performance and, critically, in sensitivity to early-stress states. This supports the argument that relying solely on environmental thresholds (e.g., temperature, humidity, EC and pH) may miss or delay the detection of incipient stress, particularly when environmental parameters remain within broad “acceptable” ranges due to buffering or averaging effects [4, 5, 7-9]. The classical machine learning baseline, while superior to IoT thresholds alone, still lagged behind deep learning, reinforcing the added value of automated feature learning in complex visual domains [1-3, 10, 11]. These results mirror trends reported in precision agriculture more broadly, where deep learning has become the reference approach for plant disease, pest and stress diagnostics across a range of crops and imaging configurations [1-3, 5, 10-12].

The time-to-detection analysis further highlights the agronomic relevance of the proposed approach. On average, the deep learning pipeline provided a lead time of nearly one day over IoT thresholds and even longer relative to expert visual inspection, with particularly pronounced gains for water/misting stress episodes. In aeroponic systems, where roots are fully dependent on periodic misting and nutrient supply, such lead times can be decisive for preventing irreversible damage, maintaining root function and protecting yield [7-9, 14]. The observed detection lead times are consistent with the notion that physiological stress signatures manifest in leaf reflectance and texture before major changes in environmental parameters or canopy-level symptoms become apparent [4-6, 13]. From a systems perspective, integrating image-derived early warning into the management of aeroponic greenhouses aligns with emerging AI-enabled frameworks in protected horticulture, in which sensing, prediction and control form a closed-loop to stabilise microclimate and crop status [7-9, 12].

Interpretability analyses using class activation maps provide additional confidence in the biological soundness of the model’s decisions. CAM overlays showed that the network focused on physiologically relevant regions interveinal tissue, margins and localised lesions rather than background structures or artefacts, paralleling previous reports on the use of saliency and attribution methods to validate plant stress and disease models [4, 11, 13]. In several instances, CAMs highlighted local changes that were only retrospectively recognised by experts, suggesting that deep learning can uncover weak, spatially localised signals consistent with early stress onset [4-6, 10, 11, 13]. This is particularly important for adoption, as growers and agronomists may be more willing to trust and act on model outputs when they can visualise the regions driving predictions, rather than receiving a black-box label. Such interpretability also supports future integration with automated scouting interfaces and decision-support tools [5, 7, 8, 12].

From an agronomic and economic standpoint, the integration of the deep learning pipeline into the IoT-based aeroponic platform demonstrates how AI-driven image analysis can be operationalised in real-world production-like conditions. The reduction in the proportion of plants progressing to overt stress, without compromising yield relative to published benchmarks for aeroponic fruit vegetables, indicates that early warnings can be translated into meaningful management adjustments such as finetuning misting intervals, nutrient concentration or shading strategies to stabilise plant status [7-9, 14]. These results resonate with prior studies advocating the combined use of IoT infrastructures, advanced analytics and smart control to support sustainable, high-yield protected horticulture [7-9, 12]. In the specific context of aeroponics, where growth responses to short disruptions in root-zone management can be dramatic, early detection and rapid response are arguably even more valuable than in soil-based or substrate-based systems [7-9, 14].

Nevertheless, several limitations should be acknowledged. First, the dataset, while sizeable and balanced across classes, was acquired within a single greenhouse and focused on a particular crop and set of stress protocols. Generalisation to other cultivars, lighting regimes, hardware layouts and environmental conditions remains to be validated. Prior work in plant disease detection has shown that domain shift can markedly affect model performance, underscoring the need for cross-site validation and domain adaptation strategies [1-3, 10, 11]. Second, only RGB imaging was employed; although high-resolution RGB can capture many stress-related cues, the inclusion of thermal, hyperspectral or fluorescence modalities may further enhance sensitivity, especially for stress combinations and very early physiological changes [4-6, 13]. Third, while preliminary exploration of simple temporal and 3D cues was undertaken, more sophisticated sequence models and full 3D reconstructions could better exploit the spatio-temporal structure of stress development, as suggested by recent 3D phenotyping studies [6, 13].

Future research should therefore focus on multi-site, multi-crop datasets encompassing a wider spectrum of stress scenarios, including interactions between abiotic and biotic factors, to build more generalised and robust models [1-3, 5, 10-12]. Domain adaptation and continual learning approaches may help maintain performance as greenhouse conditions, crop varieties and management practices evolve. Exploring multimodal sensor fusion combining leaf images with thermal, spectral and detailed IoT data streams offers another avenue to address challenging class boundaries, such as between early water and nutrient stress [4-7, 13]. Finally, embedding the deep learning pipeline into closed-loop control systems, where model outputs directly inform irrigation, nutrient dosing and climate set-points, could enable fully autonomous, self-optimising aeroponic production units, in line with broader AI-driven pest and crop management frameworks [7-9, 12].

In summary, this study provides strong evidence that deep learning-based leaf image analysis, tightly integrated with IoT infrastructure, can transform stress monitoring in aeroponic horticulture by delivering accurate, interpretable and timely early warnings. Building upon advances in deep learning for plant disease and stress diagnostics, imaging-based phenotyping and smart greenhouse control [1-8, 10-13], and leveraging the high-yield potential of aeroponic systems [9, 14], the proposed approach represents a significant step towards resilient, resource-efficient and AI-enabled soilless crop production.

Conclusion

The present study demonstrates that deep learning-based leaf image analysis, when tightly integrated with an IoT-enabled aeroponic platform, can substantially enhance the timeliness, accuracy and practicality of stress detection in high-value soilless horticulture, and the findings carry several concrete implications for both research and commercial practice. By showing that a carefully designed image acquisition pipeline and a suitably tuned deep learning model can detect multiple stress types well before conventional threshold-based monitoring or human visual inspection, this work underscores that leaf imagery should be treated as a primary, not auxiliary, signal in aeroponic crop management. In practical terms, growers operating aeroponic systems can begin by installing stable, fixed RGB cameras at key canopy positions and integrating them with existing sensor networks so that leaf images and environmental data are synchronised in a single dashboard. The results support adopting segmentation-based pre-processing and state-of-the-art architectures, such as Efficient Net-class models or equivalent, within farm management software rather than relying solely on simple indices or handcrafted features. From an operational standpoint, one clear recommendation is to configure the system to issue graded alerts: low-level warnings when the model first detects early stress with moderate confidence, and high-priority alarms when confidence and persistence exceed predefined thresholds, giving growers a structured way to prioritise responses. Another practical recommendation is to link specific model outputs to predefined corrective actions, such as increasing misting frequency or duration in suspected water stress, slightly adjusting nutrient concentration and monitoring root health for nutrient-related alerts, and strengthening hygiene, scouting and isolation measures when biotic stress is flagged. Because the model provides a measurable lead time over conventional methods, managers can incorporate these alerts into standard operating procedures, treating them as triggers for rapid, small adjustments rather than emergency, large-scale interventions. To sustain performance, growers and agronomists should periodically review misclassified cases, retrain models with new images from different seasons, cultivars and lighting conditions, and maintain a curated, annotated image library as a farm asset. At the same time, system designers and researchers are encouraged to build on these findings by exploring multimodal fusion with thermal or spectral sensors, evaluating generalisation across sites and crops, and embedding these models in closed-loop controllers that can automatically fine-tune misting and nutrient dosing in near real-time. Overall, the study’s outcomes suggest that adopting deep learning-based leaf image analysis is not only technically feasible but also practically valuable, enabling aeroponic growers to protect yield and quality, reduce input waste and mitigate risk through earlier, more informed and more targeted stress management decisions within their existing infrastructure.

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