Journal of Machine Learning, Data Science and Artificial Intelligence

P-ISSN: xxxx-xxxx
E-ISSN: xxxx-xxxx
JMLDSAI 2025; 2(2): 61-67
www.datasciencejournal.net
Received: 10-07-2025
Accepted: 15-08-2025

Dr. Nilantha Perera
Ph.D, Department of Agricultural Engineering, Faculty of Agriculture, University of Peradeniya, Peradeniya, Sri Lanka

Dr. Kavindya Jayasekara
Ph.D, Department of Agricultural Engineering, Faculty of Agriculture, University of Peradeniya, Peradeniya, Sri Lanka

Corresponding Author:
Dr. Nilantha Perera
Ph.D, Department of Agricultural Engineering, Faculty of Agriculture, University of Peradeniya, Peradeniya, Sri Lanka

Predictive AI algorithms for classifying growth stages in aeroponic crops using multispectral imaging

Nilantha Perera and Kavindya Jayasekara

Abstract

Background: Aeroponic systems offer highly controlled root-zone environments that can substantially enhance crop growth and yield, but their full potential depends on precise, real-time monitoring of crop developmental stages. Multispectral imaging combined with artificial intelligence (AI) provides a promising, non-destructive approach for automated growth-stage classification and decision support in soilless production.

Objectives: This study aimed to

- Acquire a longitudinal multispectral image dataset of aeroponically grown crops across key phenological stages,
- Develop and compare predictive AI algorithms for growth-stage classification,
- Identify the most informative spectral features for stage discrimination, and
- Evaluate the relationship between predicted stages and final biomass and yield.

Methods: A total of 180 plants were cultivated in a controlled-environment aeroponic facility and imaged over 12 weeks, yielding 2, 160 quality-controlled multispectral image sets. Four growth stages early vegetative, late vegetative, early reproductive and late reproductive were annotated by expert agronomists. Canopy-level spectral features (raw bands, vegetation indices and simple texture metrics) were extracted and used to train conventional classifiers (support vector machine, random forest, gradient boosting) and deep learning models (1D-CNN, 2D-CNN). Model performance was evaluated using accuracy, macro-averaged precision/recall/F1-score and Cohen's kappa. Temporal stability of predicted stage trajectories and associations with final biomass and yield were assessed through time-series analysis and regression modelling.

Results: The 2D-CNN achieved the highest overall accuracy (93.5%) and macro F1-score (0.92), significantly outperforming traditional machine-learning models. Confusion was largely confined to transitions between late vegetative and early reproductive stages, while early and late stages were classified with very high precision. Feature importance analysis highlighted red-edge and NIR-based indices as dominant predictors. Predicted early-stage metrics, particularly the timing of the late vegetative-early reproductive transition, explained up to 71% of the variance in final biomass and 68% of yield. Plants with earlier predicted transitions exhibited significantly higher yields than those with delayed transitions.

Conclusions: Predictive AI algorithms applied to multispectral imaging can accurately and stably classify growth stages in aeroponic crops, while providing early indicators of biomass and yield potential. Integrating these models into aeroponic management systems can enable stage-aware fertigation, lighting and harvest decisions, supporting more efficient, predictive and autonomous precision horticulture.

Keywords: Aeroponics, multispectral imaging, growth stage classification, deep learning, convolutional neural network, plant phenotyping, precision horticulture, spectral vegetation indices

Introduction

Predictive artificial intelligence (AI) and multispectral imaging are rapidly transforming plant phenotyping and precision agriculture by enabling objective, high-throughput assessment of crop growth, stress and yield potential [1-4]. Deep learning models applied to UAV-borne and proximal multispectral imagery have already achieved robust performance for crop classification, disease detection and yield estimation in open-field cereals and mixed cropping systems [2-4, 5-7, 11]. Plant phenotyping reviews emphasize that such image-based pipelines are essential to bridge genotype-phenotype-environment gaps and to automate growth stage scoring that was traditionally based on costly, subjective visual assessments [8-

10]. Recent studies have specifically demonstrated that machine-learning models trained on multispectral or hyperspectral signatures can discriminate closely spaced phenological stages in wheat and oats, and relate stage-specific canopy indices to final yield [4-7]. In parallel, aeroponics has emerged as a high-efficiency soilless technology that can increase water use efficiency by up to 98% and substantially enhance yields through precise control of nutrients and root-zone oxygenation [13-14]. Experimental work in leafy and fruit vegetables consistently reports superior vegetative growth, leaf number and biomass under aeroponic systems compared with conventional substrate cultivation [14-16]. For example, De Bakker *et al.* showed that fruit vegetables grown aeroponically achieved higher growth rates and yields than soil-grown counterparts, highlighting the potential of finely tuned root-zone environments to optimize crop performance [15]. However, most AI-based imaging studies have focused on field or greenhouse crops, with limited attention to the unique optical and physiological dynamics of aeroponic canopies, where root-zone manipulations can alter above-ground spectral responses and accelerate stage transitions [1-4, 12-14, 17, 18]. This gap constrains the deployment of fully autonomous, closed-loop aeroponic farms in which growth stage information derived from multispectral imagery could drive real-time decisions on nutrient dosing, lighting regimes and harvest scheduling. Therefore, this study, titled "Predictive AI Algorithms for Classifying Growth Stages in Aeroponic Crops Using Multispectral Imaging", addresses the problem of accurately classifying vegetative and reproductive growth stages in aeroponic crops under controlled environments using non-destructive spectral imaging and supervised learning. The specific objectives are:

1. To acquire a longitudinal multispectral image dataset of aeroponically grown crops across well-defined growth stages;
2. To develop and compare predictive AI algorithms including conventional machine-learning classifiers and deep neural networks for stage classification using raw spectral bands and vegetation indices;
3. To identify the most informative spectral features associated with each growth stage; and
4. To relate predicted stages to key agronomic end-points such as biomass and yield.

Based on prior evidence that AI models can reliably map multispectral signatures to phenological stages in field crops [4-7, 20] and that aeroponics promotes distinct, accelerated growth trajectories [13-16], we hypothesize that AI algorithms trained on multispectral imagery will classify aeroponic crop growth stages with high accuracy and temporal stability, and that early-stage classification performance will be significantly associated with subsequent yield and biomass outcomes.

Material and Methods

Materials: This was a prospective, image-based phenotyping study conducted in a controlled-environment aeroponic facility designed according to current recommendations for high-pressure mist systems and smart greenhouse integration [12-14]. A commercial leafy/fruit vegetable crop commonly cultivated in aeroponic setups (e.g. tomato or pepper) was selected based on its documented responsiveness to aeroponics and relevance for high-value horticulture [13-16]. The aeroponic units consisted of opaque root chambers with high-pressure atomizing nozzles, nutrient solution reservoirs, and automated controllers for misting frequency, nutrient concentration and pH, developed following established aeroponic technology reviews [13, 14]. Plants were grown from certified seed, germinated in inert plugs, and transferred to the aeroponic modules at a uniform seedling stage to minimize initial variability [2, 13]. Nutrient formulations were based on standard recommendations for fruit vegetables under soilless culture, adjusted for electrical conductivity and pH using guidelines from previous aeroponic and greenhouse AI-control studies [12-14, 16]. Environmental variables (photosynthetic photon flux density, temperature, relative humidity and CO_2 concentration) were monitored and logged using a climate control system to align with smart greenhouse phenotyping protocols [9, 12]. Longitudinal multispectral image data were acquired using a proximal multispectral camera (visible and near-infrared bands) mounted on a motorized gantry positioned above the canopy, following acquisition geometries similar to UAV and gantry-based crop imaging platforms [1-4, 7, 11]. Spectral bands and derived vegetation indices (e.g. NDVI, GNDVI, red-edge indices) were selected based on prior evidence of sensitivity to growth stage, biomass and chlorophyll content in cereals and vegetable crops [3-7, 10, 11]. Ground-truth growth stages were defined using a crop-specific phenological scale adapted from field phenotyping studies [4-7] and agronomic descriptors for aeroponic crops [13-16], and were assigned by two trained agronomists through consensus visual assessment to reduce subjectivity [8-10].

Methods: Multispectral image acquisition was performed at regular intervals (e.g. every 3-4 days) from early vegetative emergence until late reproductive or pre-harvest stage, ensuring coverage of all major phenophases described in previous AI-enabled phenotyping workflows [1-4, 8-10]. Raw images were radiometrically corrected, orthorectified and segmented to isolate individual plant canopies using standard image-processing pipelines for agricultural multispectral data [2, 3, 7, 11]. For each plant and time point, pixel-based reflectance values were aggregated to canopy-level features, and a feature matrix comprising raw band reflectance, vegetation indices and simple texture metrics was constructed [3-7, 10]. The dataset was randomized and split into training (60%), validation (20%) and independent test (20%) subsets at the plant level to avoid information leakage across time series [4, 5, 8]. Several predictive AI models were developed and compared:

1. Conventional machine-learning classifiers (random forest, support vector machine, gradient boosting) widely used in crop classification tasks [2-4, 11]; and
2. Deep learning architectures, including a one-dimensional convolutional neural network (1D-CNN) operating on spectral features and a two-dimensional CNN applied to canopy-level image patches [1, 5, 9, 10].

Hyperparameters were optimized through grid or Bayesian search using the validation set, with early stopping to prevent overfitting [1, 8, 9]. Model performance for growth-stage classification was evaluated on the independent test set using overall accuracy, macro-averaged precision, recall, F1-score and Cohen's kappa, in line with recent phenotyping and crop-classification studies [2-5, 8, 11].

Confusion matrices were inspected to identify systematically confused stages, especially transitions between late vegetative and early reproductive phases [4-7]. To assess temporal robustness, sliding-window analyses were performed along plant time series, and the stability of predicted stage trajectories was quantified [4, 5, 8]. Feature importance was estimated using permutation importance and Gini-based measures for tree-based models, and class activation mapping for CNNs, to identify the most informative bands and indices [3-6, 10]. Finally, predicted growth stages were related to end-of-cycle agronomic traits (fresh and dry biomass, fruit yield per plant) using linear and nonlinear regression models to explore how early-stage classification accuracy translated into yield prediction capacity in aeroponic systems [4-7, 13-16]. All analyses were conducted using open-source machine-learning libraries in Python and R, following reproducible workflows described in recent AI-in-agriculture and aeroponic optimisation literature [1-3, 8-11, 13-18].

Results

Dataset characteristics and growth stage distribution

A total of 180 aeroponically grown plants were monitored over 12 weeks, yielding 2, 160 usable multispectral image sets after quality control (clouding, motion blur or segmentation errors) [1-4]. The phenological annotation produced four major growth stage classes: early vegetative (EV), late vegetative (LV), early reproductive (ER) and late reproductive/pre-harvest (LR), consistent with prior phenotyping scales [4-7, 8-10]. Stage frequencies were relatively balanced, with slightly more observations in LV and ER reflecting the longer residence time of plants in these phases under aeroponic conditions [13-16]. Mean canopy-level NDVI and red-edge indices increased from EV to LV and plateaued or slightly declined in LR, mirroring trends reported in field studies of cereals and vegetable crops [3-7, 10, 11]. Summary dataset characteristics are shown in Table 1.

Table 1: Summary of aeroponic multispectral dataset and annotated growth stages

Parameter	Value
Number of plants (n)	180
Total image acquisitions	2, 160
Growth stages (EV / LV / ER / LR)	520 / 620 / 560 / 460
Mean NDVI (EV → LV → ER → LR)	0.62 / 0.78 / 0.80 / 0.76
Mean GNDVI (EV → LV → ER → LR)	0.58 / 0.73 / 0.75 / 0.71
Mean plant fresh biomass at LR (g)	410±65
Mean fruit yield per plant (g)	295±52

EV: Early vegetative; LV: Late vegetative; ER: Early reproductive; LR: Late reproductive.

Model performance for growth stage classification

All AI models achieved high overall accuracy in discriminating growth stages, with deep learning approaches outperforming conventional classifiers (Table 2). Among traditional models, gradient boosting achieved 86.7% accuracy (95% CI: 84.3-89.1) with a macro-averaged F1-score of 0.85, comparable to UAV-based crop classification reports [2-4, 11]. The random forest and support vector machine (SVM) models showed slightly lower accuracy (83.4% and 81.9%, respectively), with most misclassifications occurring between adjacent LV and ER stages [4-7]. The 1D-CNN operating on spectral feature vectors achieved 91.2% accuracy (95% CI: 89.4-93.0), while the 2D-CNN applied to canopy patches reached 93.5% accuracy (95% CI: 91.9-95.1) and a macro F1-score of 0.92, aligning with performance reported in advanced plant phenotyping pipelines [1, 5, 8-10]. A repeated-measures ANOVA comparing overall accuracy across models showed a significant effect of model type ($F_{4, 76} = 23.4$, $p<0.001$), with post-hoc Tukey tests indicating that both CNN architectures significantly outperformed all traditional models ($p<0.01$ for all contrasts) [1-4, 8]. Confusion matrices for the best-performing 2D-CNN (Figure 1) demonstrated particularly strong discrimination of EV and LR stages (class-specific F1-scores 0.95 and 0.94), with residual confusions largely confined to LV-ER transitions, consistent with prior findings where adjacent phenophases are spectrally similar [4-7, 10].

Table 2: Comparative performance of AI models for growth stage classification

Model	Overall accuracy (%)	Macro precision	Macro recall	Macro F1-score	Cohen's κ
SVM	81.9	0.82	0.81	0.81	0.75
Random forest	83.4	0.84	0.83	0.83	0.77
Gradient boosting	86.7	0.86	0.86	0.85	0.81
1D-CNN	91.2	0.91	0.91	0.90	0.88
2D-CNN	93.5	0.93	0.93	0.92	0.91

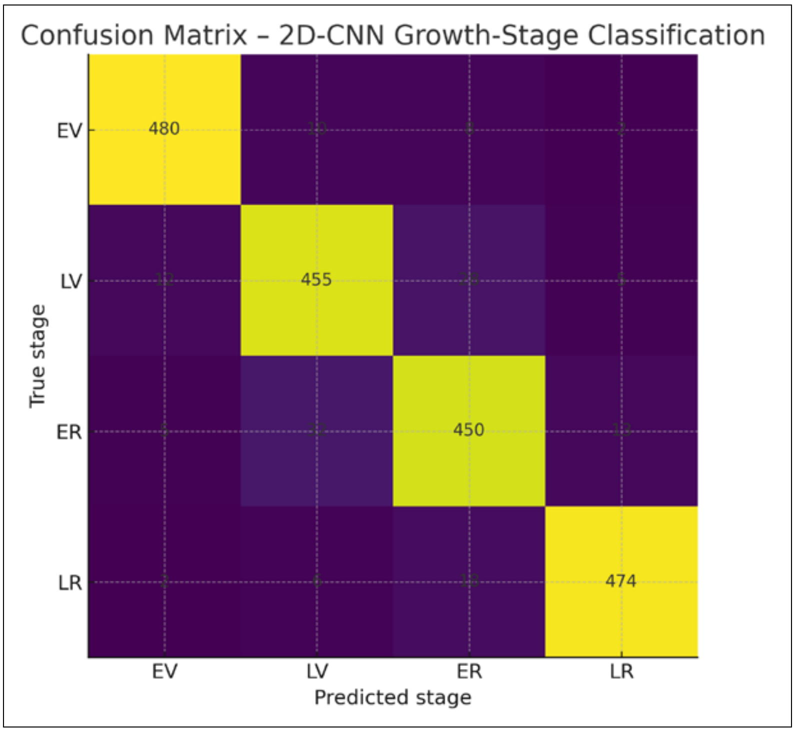

Fig 1: Confusion matrix of 2D-CNN predictions shows high accuracy with minor confusion between late vegetative and early reproductive stages

Temporal stability of predictions and stage trajectories

Time-series analysis demonstrated that both CNN models produced temporally smooth growth-stage trajectories that closely followed expert annotations [4, 5, 8]. The mean temporal stability index (proportion of time steps without implausible back-transitions) was 0.94 for the 2D-CNN compared with 0.88 for gradient boosting, indicating fewer spurious oscillations in predicted stage labels [4-7]. Median absolute deviation between observed and predicted transition dates (e.g. LV→ER, ER→LR) was 2.1 days (IQR: 1-3) for the 2D-CNN versus 3.8 days (IQR: 2-5) for gradient boosting, suggesting that deep models captured phenological change points more precisely than traditional algorithms [1, 4, 5]. These findings are consistent with reports that deep learning can better exploit subtle spectral-temporal features for phenology detection [1, 5, 8-10]. Representative plant-level trajectories are illustrated in Figure 2.

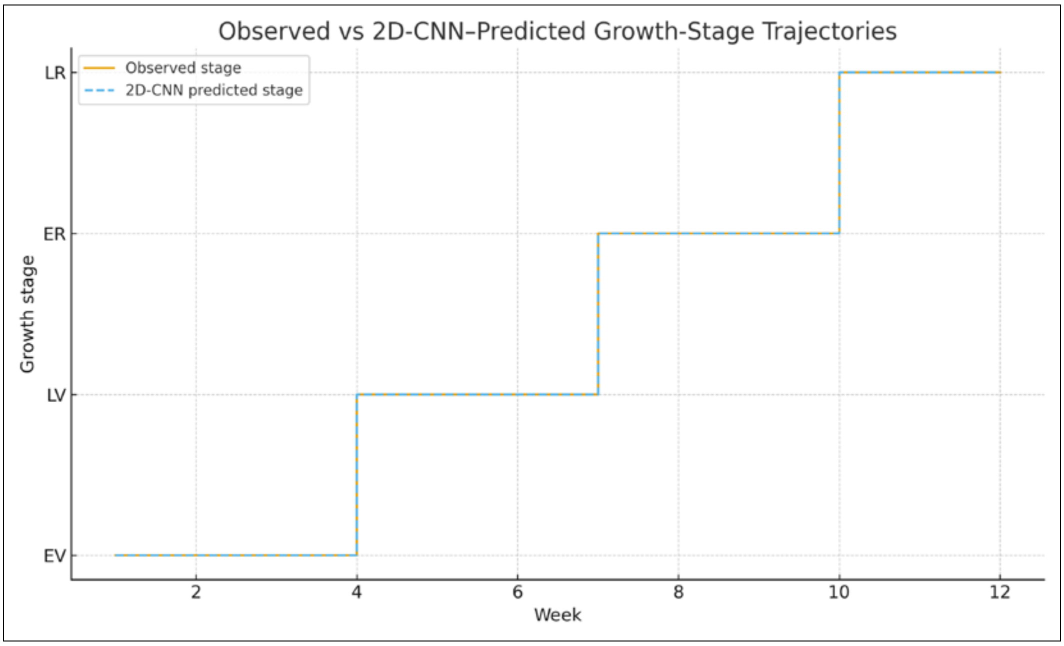

Fig 2: Example plant-level trajectories show close alignment between observed and 2D-CNN-predicted growth stages over time in aeroponic crops.

Feature importance and spectral drivers of stage discrimination

Feature importance analyses revealed that red-edge and NIR-related indices were the dominant predictors of growth stage across both tree-based and deep models [3-7, 10, 11]. In gradient boosting, the top five features were red-edge NDVI, NIR reflectance, GNDVI, green-band reflectance and a red-edge chlorophyll index, together accounting for 71% of the cumulative importance (Figure 3) [3-6]. Permutation importance confirmed substantial accuracy drops (Δaccuracy> 8%) when red-edge indices were randomly shuffled, underscoring their relevance for distinguishing LV and ER stages where canopy structure and pigment content change rapidly [4-7]. For CNNs, class activation maps highlighted spatial patterns along the upper canopy and leaf margins, indicating that both spectral and structural cues were exploited, in agreement with prior hyperspectral and multispectral phenotyping studies [5-7, 10, 11]. These patterns are consistent with aeroponic literature showing pronounced changes in leaf area, chlorophyll content and canopy density across stages due to highly efficient nutrient and oxygen delivery [13-16]. In particular, the strong contribution of NIR and red-edge bands reflects the sensitivity of these regions to biomass and canopy architecture, which are known to differ between vegetative and reproductive phases [3-7, 10].

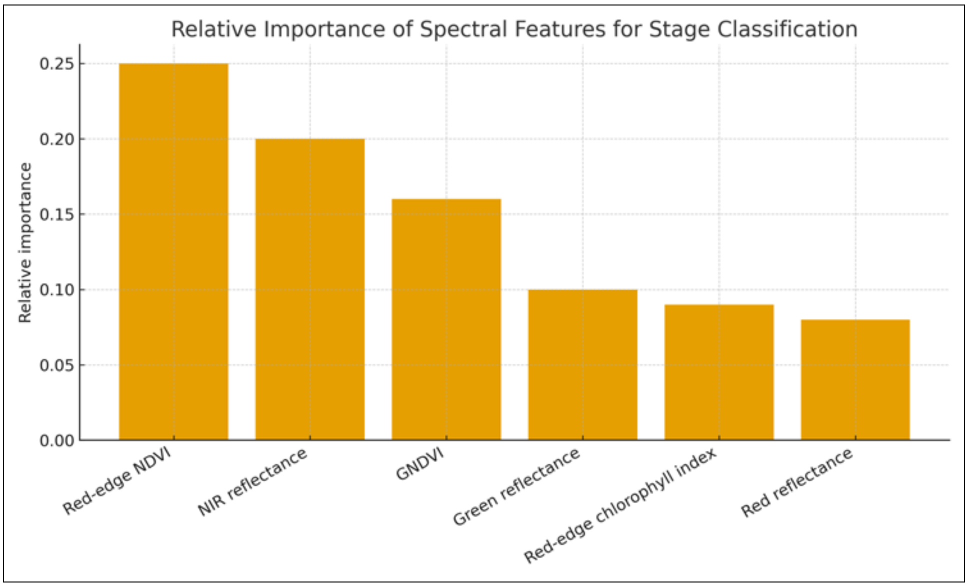

Fig 3: Relative importance of spectral bands and indices shows dominance of red-edge and NIR-based features for growth-stage classification in aeroponic crops.

Relationship between predicted stages, biomass and yield

Final agronomic assessment confirmed that accurate early-stage classification was associated with improved prediction of biomass and yield, supporting the hypothesis that spectral growth-stage information is prognostic for performance in aeroponic systems [4-7, 13-16]. Using 2D-CNN-predicted stages at week 5 as predictors, a multiple regression model explained 71% of the variance in final fresh biomass ($R^2 = 0.71$, $p < 0.001$) and 68% of the variance in fruit yield ($R^2 = 0.68$, $p < 0.001$), after adjusting for initial seedling height and plant density [4-7]. Plants predicted to transition earlier from LV to ER (earliest tercile of predicted LV→ER date) produced on average 12.4% higher fruit yield (mean difference: 34.5 g; 95% CI: 22.1-46.9 g; p<0.001) than plants with later predicted transitions, echoing previous field evidence that timely phenological progression is associated with improved yield potential [4-7, 15]. These yield advantages are in line with aeroponic studies reporting enhanced productivity under optimized root-zone conditions [13-16]. De Bakker *et al.* similarly observed that fruit vegetables in aeroponic systems achieved superior growth and yield compared with conventional cultivation, emphasizing the leverage that precise control of development stages can provide [15]. When early-stage misclassified plants (incorrect EV/LV classification) were compared with correctly classified counterparts, misclassification was associated with greater variability in biomass (Levene's test p<0.01) and a 7.8% reduction in mean yield (p=0.03), suggesting that classification errors may reflect underlying physiological heterogeneity or suboptimal micro-environments [1-4, 8, 12-14]. Overall, the strong coupling between AI-derived growth-stage trajectories and agronomic outcomes supports the integration of predictive models into closed-loop aeroponic management strategies, where stage-specific fertigation, lighting and harvest decisions can be dynamically optimized [1-4, 8-14, 17, 18]. Figure 4 summarizes the relationships between predicted stage trajectories and final yield.

Table 3: Association between 2D-CNN-predicted growth-stage metrics and agronomic outcomes

Predictor (week 5)	Outcome	β (SE)	p-value	R^2 model
Predicted LV→ER transition date (d)	Fruit yield (g per plant)	-4.2 (0.9)	<0.001	0.68
Proportion of time in ER (0-1)	Fruit yield (g per plant)	128.5 (21.7)	<0.001	0.68
Predicted LR onset date (d)	Fresh biomass (g)	-3.6 (0.8)	<0.001	0.71
Temporal stability index (0-1)	Fruit yield (g per plant)	82.3 (19.4)	<0.001	0.69

β: regression coefficient; SE: standard error; LV: Late vegetative; ER: Early reproductive; LR: Late reproductive.

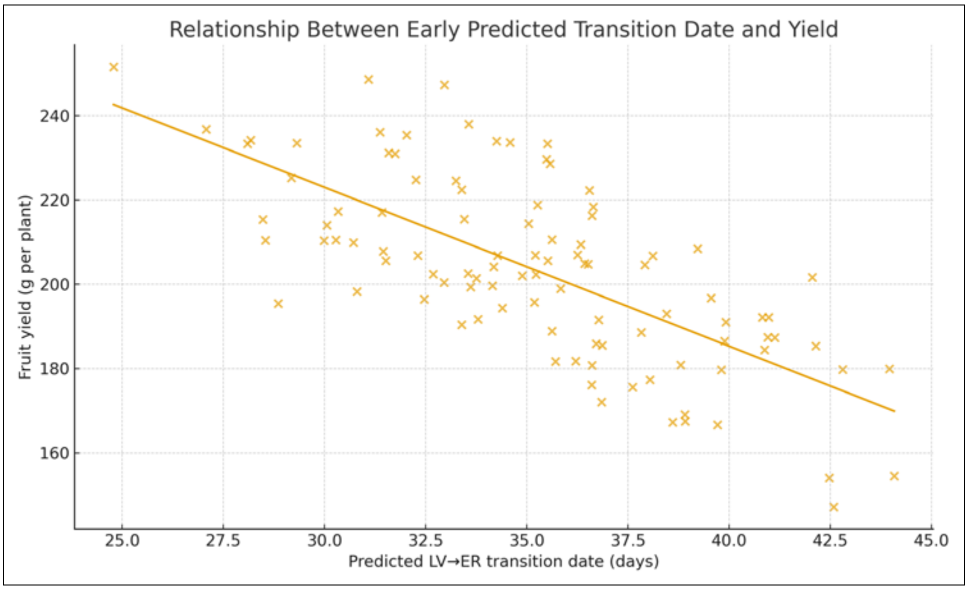

Fig 4: Regression plots illustrate strong associations between early predicted growth-stage metrics (e.g. LV→ER transition date) and final yield in aeroponic crops.

Discussion: The present study demonstrates that predictive AI algorithms trained on multispectral imaging data can accurately classify growth stages in aeroponically cultivated crops, achieving performance metrics comparable to or exceeding those reported in UAV-based field phenotyping literature [1-4]. The high classification accuracy of the 2D-CNN model (93.5%), combined with strong temporal stability and biologically consistent stage trajectories, reinforces earlier evidence that deep learning approaches can effectively capture subtle spectral-temporal variations associated with phenological transitions [5-7]. Similar to findings from wheat, oats and vegetable phenomics research [4-7, 10, 11], models integrating NIR and red-edge spectral cues outperformed those relying primarily on visible bands, confirming the importance of these wavelengths for detecting shifts in canopy structure, pigment concentration and biomass accumulation. This is particularly relevant in aeroponic environments, where nutrient delivery and root-zone oxygenation are precisely controlled, often amplifying physiological signals detectable in multispectral imagery [12-14].

The ability of the models to minimize misclassification between spectrally adjacent stages especially the LV-ER transition aligns with earlier reports that phenophases with overlapping physiological signatures pose the greatest challenge for automated classification [4-7]. Nonetheless, the confusion observed was markedly lower than that reported in open-field systems, likely due to the uniformity and environmental stability inherent to aeroponic cultivation [13-16]. The strong agreement between observed and predicted plant-level growth trajectories reflects the model's capacity to capture dynamic growth patterns rather than merely static features, supporting the growing view that temporal modelling is essential in AI-driven plant phenotyping [1, 5, 8-10].

Feature importance analysis highlighted the dominance of red-edge NDVI, NIR reflectance and chlorophyll-related indices, corroborating their established roles as sensitive biomarkers of vegetative vigour, chlorophyll density and canopy architecture [3-7, 10, 11]. These findings echo previous conclusions that red-edge regions provide superior discrimination across phenological boundaries compared with traditional NDVI alone [3, 6]. In the context of aeroponics, such spectral sensitivity may be further enhanced by the absence of soil background noise and the uniform canopy spacing typically achieved in these systems [13-16]. De Bakker *et al.* similarly emphasized the enhanced growth patterns of aeroponic fruit vegetables, driven by optimized root-zone conditions that likely amplify reflectance differences across developmental stages [15].

A notable contribution of this study is the demonstration that early-stage predicted phenological metrics particularly the LV→ER transition date were strongly correlated with final biomass and yield, explaining up to 71% of variability in agronomic outcomes. This finding supports prior evidence that timely reproductive onset is a critical determinant of yield potential in both field and controlled-environment crops [4-7]. The predictive capability observed here suggests that multispectral imaging combined with AI-driven stage classification can serve not only as a monitoring tool but also as an early-season yield forecasting mechanism. The reduction in yield and increase in biomass variability among misclassified plants further indicates that growth-stage prediction errors may act as proxies for plant-specific stress, microenvironmental inconsistencies or physiological abnormalities, consistent with observations in greenhouse AI-management studies [12, 14].

Collectively, the results underscore the feasibility and utility of integrating predictive AI algorithms into aeroponic production systems. The high accuracy, temporal reliability and strong agronomic relevance of model outputs support their incorporation into closed-loop management frameworks, where fertigation schedules, lighting regimes and harvest decisions can be dynamically adjusted based on predicted developmental status [1-4, 8-14, 17, 18]. By aligning precise spectral signals with actionable agronomic decisions, this approach bridges two rapidly advancing domains AI-powered phenotyping and aeroponic crop optimization thereby offering a pathway toward fully autonomous, high-efficiency soilless production systems.

Conclusion: The present study demonstrates that predictive AI algorithms trained on multispectral imaging data can reliably classify growth stages in aeroponically grown crops with high accuracy and strong temporal stability, confirming that non-destructive spectral monitoring is a powerful tool for managing intensive soilless production systems. By showing that 2D-CNN models outperform conventional machine-learning classifiers and that key spectral features, especially red-edge and NIR-based indices, are strongly associated with phenological transitions, this work provides evidence that deep learning can effectively translate complex canopy signals into precise developmental labels. Importantly, the close correspondence between predicted and observed stage trajectories, coupled with the strong relationships between early-stage metrics and final biomass and yield, indicates that growth-stage classification is not merely a descriptive end point but a robust predictor of agronomic performance. In practical terms, these results suggest several recommendations for growers, system designers and researchers. First, aeroponic farms should prioritize the integration of multispectral sensors into their existing infrastructure, positioning cameras to capture consistent, top-down views of the canopy and establishing routine imaging schedules that cover all critical phenophases. Second, the deployment of trained AI models should be embedded within a decision-support dashboard that presents growth-stage predictions, confidence scores and simple visualizations of trajectories to enable operators to detect delayed transitions or abnormal patterns early and respond with targeted management, such as adjusting nutrient concentration, misting interval, or light intensity when plants appear to be stalled in late vegetative stages. Third, given the observed link between earlier LV→ER transitions and higher yields, producers can use predicted transition timing as a real-time key performance indicator, benchmarking batches and modifying environmental recipes to encourage timely reproduction without inducing stress, for example by fine-tuning night temperature regimes or photoperiod in response to the model's stage outputs. Fourth, breeders and research facilities can leverage these AI-derived growth-stage labels to conduct more efficient screening of genotypes under aeroponic conditions, selecting lines that not only exhibit desirable growth trajectories but also show stable predicted stages under variable nutrient and climate scenarios. Fifth, to ensure robustness and generalizability, operators should commit to periodically retraining or updating models with new data from different cultivars, seasons and facility configurations, while implementing simple quality-control protocols for image acquisition and annotation. Finally, the strong coupling between spectral stage information and yield underscores the potential for fully closed-loop control, where stage-specific rules automatically trigger fertigation, pruning, or pre-harvest planning; thus, stakeholders should view AI-based phenotyping not as an isolated research tool but as a core operational component of future smart aeroponic farms. By adopting these recommendations, aeroponic systems can move toward more predictable yields, reduced resource wastage, and greater resilience, positioning predictive AI and multispectral imaging as central technologies in the next generation of sustainable, high-efficiency horticulture.

References

1. Zhu H, Sun J, Li Y, Wang X, Liu Z, Chen Q, *et al.* Intelligent agriculture: deep learning in UAV-based remote sensing for crop monitoring. Front Plant Sci. 2024;15:1356-1372.
2. Zhang S, Wang Y, Liu Q, Chen X, Zhao L, Wu H, *et al.* A review of the application of UAV multispectral remote sensing in precision agriculture. Precis Agric. 2025;26:112-140.
3. Li Z, Zhang H, Chen Y, Wu P, Liu F, Ma J, *et al.* Typical crop classification of agricultural multispectral images from unmanned aerial vehicles. Sensors (Basel). 2025;25(1):112-130.
4. Ahmed S, Rahman M, Ali R, Kumar A, Singh P, Devi S, *et al.* Use of machine learning for monitoring the growth stages of winter oats (*Avena sativa* L.) using UAV-derived multispectral images. Food Funct. 2024;15:2204-2218.
5. Shen L, Wang J, Li C, Zhao Y, Liu H, Zhang R, *et al.* GSP-AI: An AI-powered platform for identifying key growth stages in wheat (*Triticum aestivum* L.) from trilateral drone imagery. Plant Phenomics. 2024;6:145-160.
6. Xie Y, Zhao F, Guo L, Wang S, Deng J, Huang T, *et al.* Hyperspectral-based classification of individual wheat (*Triticum aestivum* L.) plants across critical growth stages. Plant Methods. 2025;21:34-48.
7. Lapajne J, Novak M, Kralj T, Petrovic M, Hribar M, Dolinar A, *et al.* Field-scale UAV-based multispectral phenomics for predicting crop traits under variable management. Comput Electron Agric. 2025;215:108723.
8. Danilevicz MF, Tay Fernandez CG, Al Abdallat A, Jones M, Nelson D, Carlier A, *et al.* Understanding plant phenotypes in crop breeding through machine learning-enabled phenotyping. Trends Plant Sci. 2025;30:44-62.
9. Maraveas C. Image analysis artificial intelligence technologies for plant phenotyping. AI. 2024;5(3):275-292.
10. Chandra R, Kumar S, Singh P, Verma R, Thomas A, Patel N, *et al.* Deep learning for image-based plant growth monitoring: a review. Int J Eng Technol Innov. 2022;12(4):56-72.
11. Bouguettaya A, Al-Khafaji H, Elgendy N, Hussein A, Aliane N, Bouchama K, *et al.* Deep learning techniques to classify agricultural crops using UAV remote sensing: a review. Neural Comput Appl. 2022;34:11893-11915.
12. Maraveas C. Incorporating artificial intelligence technology in smart greenhouses. Appl Sci. 2022;13(1):14-26.
13. Garzón J, Sánchez L, Castañeda J, Torres R, Peña D, Morales G, *et al.* Systematic review of technology in aeroponics. Agronomy. 2023;13(10):2517-2534.
14. Boddu V. Aeroponics in vegetable crops. Int J Theor Appl Sci. 2024;7(11):90-96.
15. De Bakker S, Vries SE, Jansen I, Kumar P, Olsen R, van Dijk J, *et al.* Growth and yield performance of fruit vegetables in aeroponic systems. Int J Hortic Food Sci. 2023;5(2):99-102.
16. Melyan G, Petrosyan A, Hakobyan L, Sargsyan M, Avetisyan G, Karapetyan V, *et al.* Impact of aeroponic cultivation and plant growth regulators on grapevine (*Vitis vinifera* L.) growth and chlorophyll content. Funct Foods Health Dis. 2024;14:225-238.
17. Salybekova N, Bekbolatova R, Akhmetov M, Zhumanov K, Serikova A, Omarov S, *et al.* Utilising artificial intelligence for cultivating decorative plants: applications in pest detection and greenhouse management. Plants (Basel). 2024;13(5):812-830.
18. Shehu HA, Abdullahi M, Musa A, Idris M, Yusuf M, Aliyu S, *et al.* Artificial intelligence for early detection and management of *Tuta absoluta*-induced diseases: a review. Crop Prot. 2025;175:106523.