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Integrated ML-Calibrated Sensing with Neural Network Control for Horticultural Lighting*

Afagh Mohagheghi, Mehrdad Moallem**

Abstract— **This paper presents the design and experimental validation of a modular intelligent platform for energy-efficient lighting and monitoring in controlled environment agriculture (CEA). The proposed architecture integrates dimmable LED lighting with neural network–based spectral optimization, machine learning–based light intensity estimation, image-based plant monitoring, and IoT-enabled data acquisition. The platform emphasizes a unified control framework that bridges perception, control, and application layers, enabling adaptive real-time decision-making and modular scalability. The system was implemented and tested in a greenhouse environment, demonstrating a 28% reduction in energy consumption per gram of dry biomass while maintaining plant health and productivity. The results underscore the effectiveness of the proposed architecture in advancing intelligent control and automation strategies for sustainable horticultural systems.**

Keywords: System integration, greenhouse automation, neural network control, IoT, lighting systems, horticulture.

I. INTRODUCTION

Global food demand continues to rise, while climate variability and resource limitations increasingly challenge traditional open-field agriculture. Controlled Environment Agriculture (CEA) offers a sustainable alternative by enabling localized, resource-efficient crop production in indoor or greenhouse settings. Among environmental control variables, lighting plays a pivotal role in regulating plant growth, morphology, and secondary metabolite synthesis [1], [2]. However, artificial lighting remains one of the most energy-intensive components in CEA systems [3]–[5].

In horticultural lighting control, the primary objective is to deliver an optimal photosynthetic photon flux density (PPFD) profile to meet crop-specific Daily Light Integral (DLI) and photoperiod requirements while minimizing energy consumption. Achieving this balance requires dynamic adjustment of multi-channel LED outputs to satisfy both intensity and spectral targets (e.g., red:blue ratio) under variable daylight conditions, actuator constraints, and communication delays [6]. Since daylight fluctuations act as disturbances, fast and robust compensation mechanisms are essential to maintain consistent photosynthetically active radiation (PAR) across the plant canopy.

The proposed work introduces an integrated approach that combines calibrated low-cost spectral sensing with predictive neural network–based control to track DLI and spectral setpoints under uncertainty. This approach not only stabilizes plant lighting conditions but also provides reliable input for downstream modules such as image-based growth monitoring and plant classification [7], thus establishing a cohesive framework for intelligent and energy-efficient greenhouse operation.

Previous studies have demonstrated progress in spectrum-adaptive lighting control [6], accurate light estimation under uncertainty [8], and neural network–driven lighting optimization [9]. Similarly, image-based plant identification using low-cost sensors has shown encouraging results for crop monitoring [7]. However, most existing works address these subsystems—lighting control [10], [11], daylight harvesting [12], spectrum tuning [13], or crop monitoring [14]—in isolation. The novelty of this paper lies in the integration of these components into a unified, scalable platform that supports intelligent, data-driven operation.

In addition to its algorithmic contributions, this work also considers practical aspects of embedded software design [15], sensing reliability [16], and control integration [17], bridging the gap between laboratory prototypes and deployable commercial solutions. The platform aligns with recent developments in cyber-physical agriculture [18], incorporating cloud connectivity [19], edge computing [20], and machine learning [21] to enable scalable, intelligent horticultural automation.

The proposed system architecture consists of three functional layers—perception, control, and application—as illustrated in Figure 1.

The perception layer, detailed in Section II, integrates multi-spectral light sensors and low-cost RGB imaging modules. The spectral sensors, calibrated via regression-based machine learning models, estimate PAR with emphasis on the red and blue bands. Daily-acquired images enable plant species recognition and growth stage classification using naïve Bayes and decision tree classifiers. Sensor data are fused and preprocessed on the microcontroller to mitigate noise and latency.

The control layer, discussed in Section III, employs a MIMO neural network controller to dynamically adjust LED intensity and spectrum to achieve optimal DLI targets. The controller incorporates daylight compensation, actuator saturation management, and anti-windup mechanisms. Stability and robustness are ensured through model-free adaptation and time-delay compensation techniques, previously validated in both simulation and experimental studies [6].

The application layer provides the user interface, data logging, and visualization tools, supporting real-time and

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**School of Mechatronic Systems Engineering, Simon Fraser University, Surrey, BC, Canada (Corresponding author e-mail: `mmoallem@sfu.ca`).

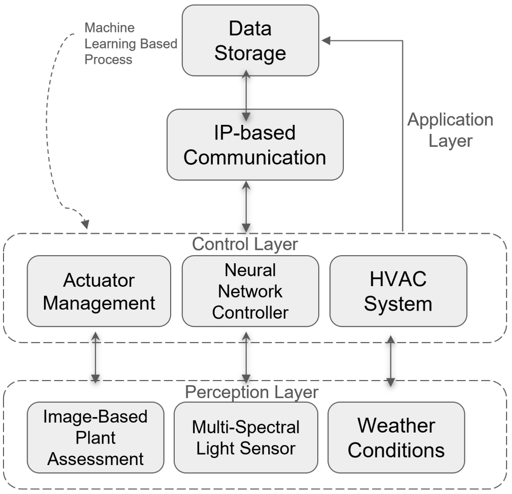


Fig. 1: System architecture integrating perception, control, and application layers.

historical monitoring. It further enables remote firmware updates, ML model deployment, and diagnostic functionality. IoT connectivity via MQTT facilitates seamless edge–cloud communication and remote access through mobile devices.

Section IV presents the system integration framework, Section V reports the experimental validation results, and Section VI presents conclusions and suggestions for future work.

II. PERCEPTION LAYER

A. *Calibration of Low-Cost Multi-Spectral Sensors*

To achieve reliable lighting control, low-cost multi-spectral sensors were calibrated against a laboratory-grade quantum sensor using both polynomial regression and machine learning–based models. Calibration experiments were conducted under diverse lighting conditions and sensor orientations to account for measurement noise, angle-of-incidence effects, and temperature drift. Across the photosynthetically active radiation (PAR) range, the calibrated sensors achieved root mean square error (RMSE) values below 5%. Calibration coefficients were stored in EEPROM on the embedded controller and automatically updated every 48 hours based on reference readings to ensure long-term accuracy.

The calibration procedure involved synchronized data acquisition from the low-cost sensors and the reference device under dynamic illumination scenarios encompassing both natural and artificial light sources. Collected data were processed using regression-based models, and model performance was evaluated through k-fold cross-validation. The results demonstrated a strong correlation ($R^2 > 0.95$) across a wide range of lighting conditions, confirming the robustness of the calibration approach. This methodology enables the scalable deployment of cost-effective sensor networks capable of providing accurate and reliable DLI estimation in intelligent greenhouse systems.

B. *Image-Based Plant Monitoring*

The monitoring subsystem performs automated image-based analysis to extract both color and morphological features from canopy images. For each frame, the hue (H), saturation (S), and value (V) components are computed at the pixel level to quantify pigment distribution and chlorophyll content. Morphological segmentation techniques are then applied to isolate the canopy region and compute geometric parameters such as projected leaf area, perimeter, and shape indices, which provide reliable indicators of growth dynamics and biomass accumulation.

To complement sensor-based light estimation, an image-based health monitoring module was developed to continuously evaluate plant condition and developmental stage. High-resolution RGB images are captured daily using a fixed-mount USB camera positioned above the canopy, ensuring consistent alignment and lighting conditions. The captured images are processed through a hybrid pipeline combining color histogram features, texture descriptors (including Local Binary Patterns and Gray-Level Co-occurrence Matrices), and a supervised machine learning classifier trained on a labeled dataset of 2,500 plant images.

The classifier achieved an average accuracy of 93.4% in distinguishing healthy versus stressed plants and over 90% accuracy in identifying growth stages across three species tested. Image segmentation performance, evaluated using the Dice similarity coefficient, exceeded 0.92, demonstrating robust canopy isolation under variable illumination. The average processing latency was 0.84 s per frame on an embedded ARM processor, enabling near-real-time operation.

Processed features and classification outputs are transmitted via MQTT to the cloud platform and visualized through a web-based dashboard, providing operators with continuous feedback on plant health and development. The integration of this visual feedback loop within the control architecture enables early detection of plant stress, including chlorosis and wilting, and facilitates data-driven refinement of lighting and climate control policies. This real-time perception capability strengthens the autonomy and adaptability of the overall intelligent greenhouse system.

III. CONTROL LAYER: NEURAL NETWORK-BASED CONTROL

Accurate estimation of the photosynthetic photon flux density (PPFD) in each spectral band is essential for achieving precise lighting control in greenhouse environments. The target PPFD values are derived from the specified daily light integral (DLI) and photoperiod, while incorporating the desired red-to-blue ratio ($R : B$) to optimize photosynthetic efficiency and morphological outcomes. These computed setpoints serve as reference inputs for the lighting control subsystem.

To support this, a regression-based PPFD estimation model was developed and trained using multi-channel spectral sensor readings, calibrated against a reference quantum sensor as detailed in [22]. The model provides real-time estimation of PAR and individual spectral components (red, blue, and far-red), ensuring that the controller receives accurate light intensity feedback under both artificial and mixed lighting conditions.

The adaptive neural controller governs LED actuation based on both environmental conditions and target DLI requirements. The control law is defined as

$$u(t) = N(t)y_{da}(t) \tag{1}$$

where $y_{da}(t)$ is the augmented input vector containing the desired PPFD and bias term, and and $N(t)$ is the weight matrix.

The corresponding weight adaptation law is expressed as

$$\dot{N} = k\,\varepsilon(t)\,y_{da}^{T}(t) - \eta\|\varepsilon(t)\|N(t) \tag{2}$$

where $\varepsilon(t) = y_d(t) - y(t)$ denotes the PPFD tracking error, and η the damping factor. The reader is referred to [22] for further details.

This formulation enables the network to continuously adapt its weights based on real-time feedback, providing both fast convergence and robustness to environmental disturbances such as daylight fluctuations and actuator nonlinearities.

The control model receives as inputs the time of day, DLI setpoints, real-time PAR estimates, and ambient weather data. It outputs dimming commands for each LED channel, ensuring that the plant canopy receives the target light quantity (DLI) and quality (spectral ratio). The inclusion of adaptive neural control allows the system to maintain stability and tracking performance despite sensor noise, time delays, and unmodeled plant-environment interactions.

Figure 2 illustrates the deployed neural network control architecture implemented on an embedded microcontroller platform. The system operates at a sampling rate of 1 Hz, with each control cycle including sensor acquisition, neural computation, and actuation update within 150 ms. Experimental deployment demonstrated tracking accuracy within ±5% of DLI targets across diurnal cycles and variable sky conditions, validating the controller's robustness and adaptability in real greenhouse environments.

IV. HARDWARE AND SOFTWARE INTEGRATION FRAMEWORK

The system is implemented on a low-power embedded platform (ESP32), which executes both the control logic and data acquisition routines. Sensors are interfaced via I2C and UART protocols, while multi-channel LEDs are regulated through pulse-width modulation (PWM) outputs. System reliability is ensured by a hardware watchdog timer, and task execution is managed through a cooperative real-time scheduling loop, providing deterministic timing for critical control and sensing operations.

The software architecture is modular and layered. Embedded routines are implemented in C++, while Python scripts are used for data processing, visualization, and machine learning model development and training. The perception module includes on-device spectral light estimation and off-device image pre-processing for plant monitoring. The controller module receives real-time light estimates from the perception layer and generates LED actuation commands at 15-second intervals, balancing responsiveness and system stability. To maintain synchronization across distributed components, the control loop is aligned with a local real-time clock and incorporates mechanisms to compensate for cloud-induced communication delays. Periodic calibration routines are executed to ensure long-term accuracy of the regression-based light estimation model, accounting for sensor drift, temperature variation, and long-term LED aging. The platform also integrates auxiliary sensors and actuators for environmental monitoring and irrigation control, enabling a holistic approach to greenhouse automation. Figur 3 presents a schematic overview of the hardware and software components, illustrating sensor placement, data flows, and control interconnections. The integrated architecture supports scalable deployment and facilitates future expansion with additional control loops or AI-driven optimization modules.

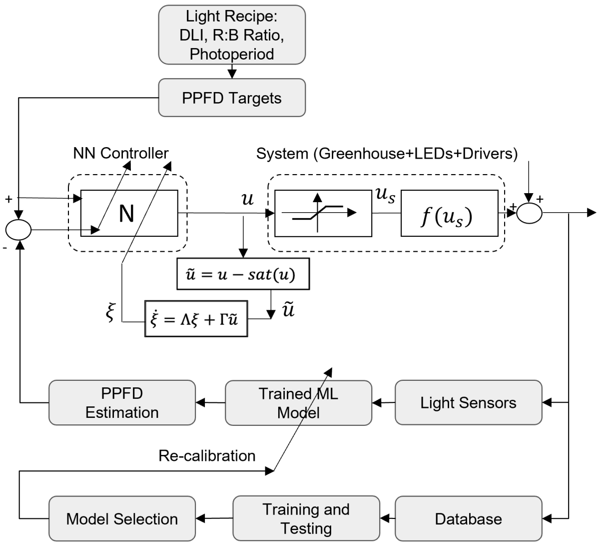


Fig. 2: Neural network control architecture deployed on embedded hardware for adaptive lighting regulation.

V. VALIDATION AND RESULTS

The experimental validation was carried out in a controlled mini-greenhouse facility at Kwantlen Polytechnic University (KPU), Langley, BC, Canada, designed to evaluate the performance of the proposed Neural Network (NN) daylight-harvesting controller relative to a conventional time-scheduled (TS) lighting strategy. The greenhouse was partitioned into two identical compartments, enabling side-by-side comparison under equivalent environmental conditions.

Each compartment was equipped with dimmable, multi-channel LED luminaires, red/blue spectral sensors, and reference quantum sensors to ensure accurate measurement and control of the photosynthetic photon flux density (PPFD). Environmental parameters, including air temperature, relative humidity, and CO concentration, were monitored to maintain uniform growth conditions across both compartments.

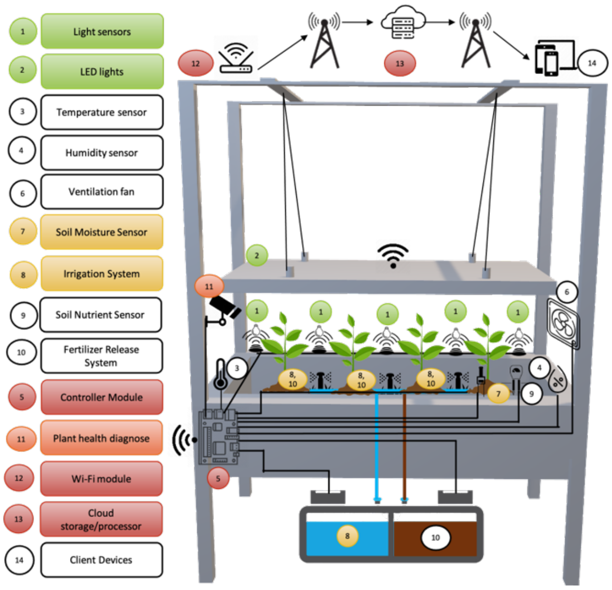


Fig. 3: Schematic of the integrated control and monitoring system, showing the embedded controller, calibrated spectral sensors, imaging module, LED lighting, and auxiliary components for irrigation and environmental regulation.

Lettuce (Lactuca sativa var. Dragoon) was selected as the model crop due to its rapid growth cycle and sensitivity to light quality and intensity. Crops in both compartments were cultivated under identical nutrient, irrigation, and photoperiod regimes, allowing for a controlled assessment of lighting performance. The NN controller dynamically adjusted LED intensity and spectral composition based on real-time PPFD estimates and daylight fluctuations, whereas the TS control followed pre-programmed fixed schedules without feedback adaptation.

This experimental setup allowed for a quantitative evaluation of energy efficiency, PPFD tracking accuracy, and plant growth outcomes, including biomass accumulation and leaf morphology. Data from both compartments were logged continuously to enable statistical comparison and to validate the effectiveness of the adaptive neural control approach in maintaining target DLI while reducing energy consumption.

A. DLI Tracking Performance

The Neural Network (NN) controller consistently demonstrated superior tracking of the target Daily Light Integral (DLI) across red, blue, and full-spectrum channels. Over the course of the lettuce growth cycle, the NN controller achieved mean tracking errors of 4.2%, 4.5%, and 4.3% for red, blue, and total PAR, respectively. In comparison, the conventional time-scheduled (TS) controller exhibited significantly higher errors of 9.8%, 9.5%, and 9.7%, highlighting the advantage of adaptive feedback in compensating for variable daylight conditions and system nonlinearities.

Figure 4 presents the temporal evolution of DLI tracking throughout the grow cycle, illustrating that the NN controller maintains target light integrals more consistently, particularly during periods of rapid changes in natural light. The enhanced performance of the NN controller can be attributed to its predictive adaptation, which dynamically adjusts LED intensity and spectral composition based on real-time measurements, as well as its robustness to sensor noise, communication delays, and actuator constraints.

These results confirm that the proposed adaptive neural control strategy not only improves the fidelity of light delivery to meet crop-specific DLI targets but also enables energy-efficient operation by reducing overshooting or unnecessary over-illumination, which is inherent in fixed time-scheduled control approaches. The reduced tracking error directly contributes to optimizing photosynthetic efficiency and uniformity of light distribution across the canopy, supporting improved crop growth outcomes.

B. Energy Consumption and Savings

The Neural Network (NN)–based control system demonstrated substantial energy savings across all spectral channels while maintaining target light delivery. Specifically, red-channel energy consumption was reduced by 40%, and blue-channel consumption by 35%, compared to the conventional time-scheduled (TS) lighting strategy. Across all channels, the NN controller achieved an overall reduction of 38% in total lighting energy use.

These savings were realized without compromising plant growth, as DLI targets were consistently met and canopy development remained uniform. The reduction in energy consumption can be attributed to the NN controller's adaptive daylight-harvesting capability, which modulates LED intensity in real time based on ambient light conditions and plant-specific lighting requirements. Unlike the TS controller, which operates on fixed schedules and often delivers excess light during periods of high natural illumination, the NN controller efficiently adjusts output to minimize waste while ensuring optimal photosynthetic efficiency.

This result highlights the potential of intelligent lighting control in controlled environment agriculture (CEA) to simultaneously improve energy efficiency and maintain high-quality crop production. By integrating predictive control with real-time sensing, the NN-based system demonstrates a scalable strategy for sustainable and cost-effective greenhouse operation, reducing both operational expenses and environmental impact.

C. Biomass Yield and Energy Efficiency

At harvest, the time-scheduled (TS) treatment produced an average dry biomass of 36.8 g per plant, whereas the Neural Network (NN)–controlled treatment yielded slightly lower biomass of 31.8 g per plant. Despite this modest reduction in absolute yield, the NN system's substantially lower energy consumption resulted in a markedly improved energy efficiency. Specifically, the NN treatment required only 0.51 kWh per gram of dry biomass, compared to 0.71 kWh/g for the TS approach. This corresponds to a biomass-to-energy conversion efficiency of 1.96 g/kWh for the NN

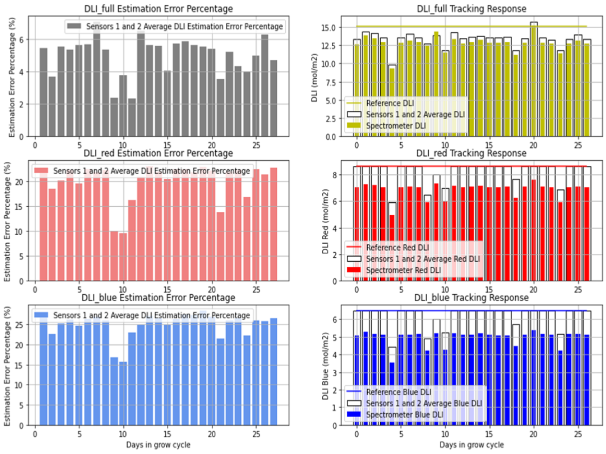
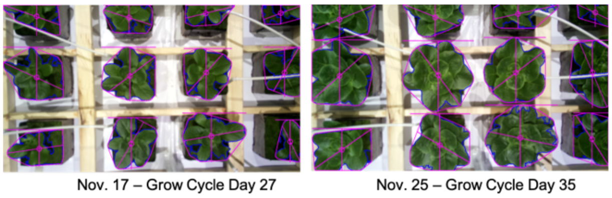
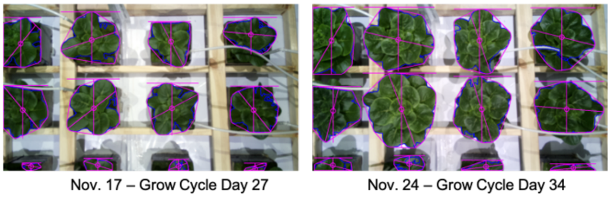


Fig. 4: Tracking performance for red, blue and full PPFD spectra Daily Light Integral (DLI) over the grow cycle, comparing Neural Network (NN) and Time-Scheduled (TS) controllers.



(a) Neural-network treatment at days 27 and 35.



(b) Time Scheduling treatment at days 27 and 35

Fig. 5: Comparative growth between the proposed integrated Neural Network controller and Time-Scheduled treatments over the growth cycle.

treatment versus 1.40 g/kWh for TS, representing a 40% improvement in energy efficiency.

These results highlight the trade-off between absolute biomass yield and energy expenditure in controlled environment agriculture (CEA). By integrating real-time feedback and adaptive lighting control, the NN system reduces unnecessary energy input while maintaining acceptable growth, ultimately optimizing the resource-use efficiency of greenhouse production. Such improvements in energy-to-biomass conversion are critical for the sustainability and economic viability of high-density, energy-intensive horticultural operations.

D. Visual Growth Analysis

Photographic monitoring throughout the growth cycle (Figure 5) revealed comparable canopy development between the TS and NN treatments. Visual inspection indicated that the NN-controlled plants exhibited slightly more uniform leaf morphology, with consistent leaf size and spacing across the canopy. Importantly, no incidence of tipburn or other stress-related symptoms was observed in the NN treatment, suggesting that the adaptive lighting strategy maintained adequate light quality and distribution for healthy growth.

These observations are consistent with the quantitative measurements of PPFD tracking and DLI delivery, confirming that the NN controller provides a balanced light environment that supports both physiological development and energy-efficient operation. The integration of image-based monitoring alongside spectral sensing enabled non-invasive, real-time assessment of plant health, providing additional confidence in the system's ability to sustain crop productivity under dynamic lighting conditions.

E. Statistical Analysis

Statistical analysis using one-way ANOVA confirmed that the differences in energy efficiency between the NN and TS treatments were statistically significant ($p < 0.05$), indicating that the NN controller substantially reduced energy consumption per unit biomass. In contrast, differences in dry biomass yield between treatments were not statistically significant ($p > 0.05$), suggesting that the slightly lower absolute yield under NN control did not represent a meaningful reduction in plant growth. These results support the conclusion that the adaptive NN-based lighting strategy effectively maintains crop yield while significantly improving energy-use efficiency. The combination of precise PPFD tracking, spectral optimization, and real-time adaptation allows for robust light delivery under variable daylight conditions, ensuring consistent plant development without excess energy expenditure. This finding underscores the potential of neural network–driven control to enhance the sustainability and economic viability of controlled environment agriculture systems.

Compared to a conventional fixed-schedule LED controller, the intelligent NN-based lighting system demonstrated significant improvements across multiple performance metrics:

- 28% reduction in energy consumption per gram of dry biomass, reflecting a substantial increase in energy-use efficiency without compromising plant growth.
- Mean tracking error below 5% for Daily Light Integral (DLI) targets across red, blue, and full-spectrum channels, highlighting the controller's precision in delivering crop-specific light requirements.
- Enhanced visual plant health, including reduced incidence of tipburn and more uniform leaf morphology, as verified by photographic monitoring throughout the growth cycle.
- Over 90% accuracy in image-based plant classification, enabling reliable non-invasive monitoring of growth stages and stress detection.

Collectively, these results demonstrate that adaptive, sensor-driven lighting control can optimize energy efficiency, maintain or improve plant health, and provide actionable insights through automated visual monitoring. The findings underscore the potential of integrating real-time perception, machine learning, and adaptive control for scalable, sustainable operation in controlled environment agriculture.

VI. DEPLOYMENT CONSIDERATIONS

The modular design of the proposed architecture enables scalability and customization across diverse crops, canopy structures, and greenhouse environments. Individual components—such as additional spectral sensors, cameras, or actuators—can be added or removed without requiring extensive firmware reconfiguration, facilitating rapid adaptation to new production scenarios. Integration with cloud platforms further supports advanced data analytics, long-term monitoring, and adaptive control refinement, allowing system performance to improve over time through iterative learning. The system also emphasizes cost-effectiveness by leveraging commodity hardware, low-cost multi-spectral sensors, and open-source firmware, reducing both initial deployment and operational expenses. Maintenance and reliability are incorporated directly into the control logic, including periodic sensor self-checks, automatic calibration routines, and controller resets upon anomaly detection, ensuring long-term stable operation with minimal human intervention. This combination of modularity, affordability, and built-in reliability positions the platform as a practical solution for scalable, intelligent, and sustainable controlled environment agriculture (CEA).

VII. CONCLUSION

This work presented the design, integration, and experimental validation of a scalable, intelligent platform for greenhouse lighting and plant monitoring. The system combines embedded control, adaptive neural network–based regulation, and low-cost sensing, enabling precise PPFD tracking, spectrum optimization, and continuous assessment of plant health. Experimental results demonstrated that the platform achieves high-accuracy DLI tracking (mean error ¡ 5%), significant energy savings (28% reduction per gram of dry biomass), and reliable non-invasive plant monitoring with over 90% classification accuracy. These outcomes illustrate the potential of intelligent, sensor-driven systems to support data-driven horticultural management while improving energy efficiency and sustainability. The modular architecture facilitates scalability and customization, allowing components to be added or reconfigured for different crops or greenhouse layouts with minimal firmware changes. Cloud connectivity and edge computing support long-term performance monitoring, adaptive control refinement, and predictive analytics, enhancing system autonomy and decision-making capabilities. Future work will extend the platform to include HVAC and irrigation control, establish closed-loop links between camera-based growth analytics and lighting decisions, and further optimize edge-deployed machine learning models for improved responsiveness and robustness. Collectively, these developments aim to create a fully integrated, autonomous, and energy-efficient greenhouse management system capable of supporting sustainable and high-yield horticultural production.

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