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AI-Enabled Predictive Control for Tropical Greenhouse Farming: Environmental Stability, Resource Efficiency, and Yield Improvements

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ABSTRACT

Purpose: *This study aims to evaluate the effectiveness of an AI-enabled predictive control system in enhancing environmental stability, resource efficiency, and crop productivity within tropical greenhouse farming.*

Subjects and Methods: *The research was conducted using a 4 × 6-meter greenhouse prototype integrating IoT sensors and machine learning algorithms, including Random Forest and Artificial Neural Networks. Lettuce (Lactuca sativa) served as the model crop. The AI-driven greenhouse was compared with a conventional manually operated system across a full cultivation cycle. Data collected included microclimate parameters, water and energy consumption, plant growth indicators, and final yield.*

Results: *The AI-enabled greenhouse maintained more consistent environmental conditions, keeping temperature, humidity, light intensity, and soil moisture within optimal ranges. Water use was reduced by approximately 38%, and energy consumption decreased by 13% compared to the conventional system. Plants grown under predictive control exhibited stronger vegetative growth, with notable increases in height, leaf number, and canopy size. Yield improved by nearly 30%, accompanied by higher marketable quality. Predictive models demonstrated strong accuracy, supporting reliable real-time decision-making.*

Conclusions: *The results confirm that AI-based predictive control substantially improves greenhouse performance in tropical environments, offering a sustainable and efficient solution for modern horticultural production.*

INTRODUCTION

Global agricultural systems are under increasing pressure as climate variability intensifies, natural resources become more limited, and food demand continues to rise (Vos & Bellù, 2019; Khatri et al., 2024). These pressures are particularly evident in tropical regions, where high temperatures, humidity fluctuations, and unpredictable weather patterns frequently disrupt crop productivity. In response to these challenges, controlled-environment agriculture (CEA), especially greenhouse cultivation, has emerged as a promising approach for stabilizing plant growth conditions and enhancing yield (Ojo & Zahid, 2022; Shamshiri et al., 2018). However, conventional greenhouse systems remain heavily dependent on manual adjustments and static control mechanisms, making them insufficiently adaptive in regions characterized by rapid and nonlinear environmental fluctuations.

In the past decade, technological innovations such as Internet of Things (IoT) devices and sensor-embedded systems have begun to transform greenhouse operations. By enabling real-time data collection on key environmental variables temperature, humidity, light intensity, CO_2 concentration, and soil moisture these systems provide farmers with a more comprehensive understanding of plant needs and environmental dynamics. Despite these advances, most existing greenhouse systems still rely on rule-based or threshold-driven control strategies, which lack the flexibility to respond optimally to sudden climatic variations or to anticipate future conditions.

Ben Ayed & Hanana (2021) and Ruiz-Real et al. (2020) said that, artificial Intelligence (AI), particularly machine learning and deep learning techniques, has introduced a paradigm shift in the agricultural sector. AI-driven predictive control models are capable of identifying patterns, forecasting environmental changes, and generating adaptive control decisions that surpass the capabilities of traditional systems. By integrating historical environmental data, plant growth indicators, and real-time sensor inputs, AI can optimize resource allocation and ensure that crops are exposed to consistently favorable microclimatic conditions.

The application of AI in greenhouse farming aligns with the broader movement toward precision agriculture, which emphasizes optimized resource use and data-informed decision-making (Azlan et al., 2025). Studies have demonstrated that AI-driven control systems can significantly enhance water-use efficiency, energy consumption, and crop productivity. However, most previous studies have focused on greenhouses in temperate regions, where environmental variations are relatively mild. Tropical environments present a different set of complexities higher temperatures, excessive humidity, and sudden weather shifts that require more robust and responsive control approaches.

Greenhouse farming in tropical regions faces persistent challenges in maintaining stable environmental conditions (McCartney & Lefsrud, 2018; Jensen, 2001). Excessive heat can impede photosynthesis and disrupt plant metabolism, while low humidity levels accelerate transpiration and create water stress. Conversely, overly high humidity increases the risk of fungal diseases. Similarly, insufficient or excessive light conditions can reduce photosynthetic efficiency and slow biomass accumulation. These challenges underscore the necessity of predictive and adaptive control systems that can maintain microclimatic stability despite external volatility.

AI-enabled predictive control systems address these issues by learning the complex interactions between environmental parameters and plant responses. Algorithms such as Random Forest and Artificial Neural Networks (ANN) can interpret sensor data and perform real-time predictions about plant needs, enabling precise adjustments to irrigation, ventilation, and lighting (Mekonnen et al., 2019). These systems offer the ability not only to respond to current conditions but also to anticipate future fluctuations, ensuring consistent microclimate regulation.

Resource efficiency is a critical component of sustainable agricultural development, particularly in areas where water and energy availability is limited. Ghani et al. (2019) said that, greenhouse systems frequently consume large amounts of water for irrigation and significant energy for ventilation and artificial lighting. AI-driven systems can significantly reduce unnecessary resource usage by delivering irrigation based on predicted evapotranspiration, adjusting ventilation in response to heat accumulation trends, and optimizing lighting schedules to meet crops' photosynthetic requirements without waste.

Moreover, predictive AI models can improve crop yield by aligning environmental parameters with optimal physiological conditions. For instance, maintaining temperature and humidity within specific thresholds for each growth stage supports faster development, better nutrient uptake, and increased biomass production (Walne & Reddy, 2022). AI-based systems facilitate this precision by continuously refining control strategies based on real-time performance data and plant growth outcomes.

The integration of AI into tropical greenhouse systems also offers broader socio-economic implications (Hoseinzadeh & Garcia, 2024). In many tropical countries, agricultural productivity is hindered by limited access to advanced technologies, insufficient digital infrastructure, and low technological literacy among farmers. Demonstrating the effectiveness and practicality of AI-enabled greenhouse management provides a pathway for modernizing agricultural practices in resource-constrained environments, while also improving food security (Abedalrhman & Alzaydi, 2025).

Despite the potential benefits, the implementation of AI-driven predictive control in tropical greenhouse farming remains underexplored. Few empirical studies have evaluated how such systems perform under real tropical conditions, particularly in terms of environmental stability, resource efficiency, and yield improvement (Scopel et al., 2013). This gap highlights the need for experimental validation of AI-enabled systems in real-world settings to determine their scalability and long-term feasibility.

Prototypes that integrate IoT sensors with AI algorithms serve as essential testing grounds for evaluating the functionality of predictive models. These systems provide opportunities to assess how AI responds to dynamic environmental inputs, how accurately it predicts environmental needs, and how effectively it regulates greenhouse conditions. Through such experimental setups, researchers can evaluate the degree to which AI improves microclimate stability and crop performance compared with traditional manual or rule-based controls.

Early results from experimental studies have shown promising outcomes, with AI-based systems demonstrating enhanced control precision and significant reductions in water and energy consumption (Alenezi & Alabaiadly, 2025). However, the performance of these systems in cycles of crop growth, variable weather conditions, and different plant species requires further examination. Understanding how AI models adapt over time and across conditions is essential for determining their practical utility for farmers.

Another crucial element in implementing AI-enabled greenhouse systems is the integration of predictive analytics with actuators such as fans, pumps, and LED lighting (Hanafi et al., 2024). These components must respond quickly and accurately to AI-generated commands to maintain environmental stability. Poor integration or delays in system responses can diminish the effectiveness of predictive control and lead to suboptimal plant growth. Therefore, evaluating both software performance and hardware synchronization is vital.

Given the increasing urgency for sustainable agricultural solutions in tropical regions, AI-enabled predictive control represents a transformative opportunity. By bridging the gap between environmental variability and optimal crop conditions, AI-driven systems have the potential to reshape tropical horticulture, enhancing yields while minimizing environmental impact. The growing body of research in this field indicates that such technologies can be successfully tailored to tropical climates with appropriate system design and calibration.

This study aims to contribute to the emerging literature by examining the effectiveness of an AI-enabled predictive control system designed specifically for greenhouse farming in tropical environments. Through a combination of IoT-based monitoring, machine learning algorithms, and automated actuation, this research evaluates how AI can improve environmental stability, increase resource-use efficiency, and enhance crop yield (Eze et al., 2025; Dhanaraj et al., 2025). The findings are expected to provide empirical evidence of the feasibility and benefits of implementing AI-driven smart greenhouse systems in tropical agricultural contexts.

METHODOLOGY

Research Design

This study employs an applied experimental research design, which is the most appropriate approach for evaluating technological interventions such as AI-based predictive control systems. The research focuses on developing, implementing, and testing a smart greenhouse prototype equipped with Internet of Things (IoT) sensors and Artificial Intelligence algorithms in a real-world tropical environment. Through this design, the study aims to measure the performance of the AI-enabled system by comparing environmental stability, resource-use efficiency, and crop yield against traditional greenhouse management practices. The experimental design allows for controlled conditions while still capturing natural environmental variability, ensuring that results reflect realistic growing scenarios typical of tropical agricultural settings.

System Development and Implementation

The method includes the integration of IoT sensors, actuators, and machine learning algorithms to construct an automated greenhouse control system. Sensors continuously monitor environmental parameters such as temperature, humidity, light intensity, soil moisture, and CO_2 concentration, while actuators including irrigation pumps, ventilation fans, and LED lights respond to AI-driven instructions. Historical and real-time data are used to train and operate machine learning models such as Random Forest and Artificial Neural Networks (ANN), enabling predictive control that adjusts environmental conditions before deviations from optimal ranges occur. The system is deployed on an experimental greenhouse plot, where its performance is tested across multiple crop cycles using lettuce as the model plant.

Experimental Procedure

The experimental setup consists of two greenhouse conditions: an AI-enabled smart greenhouse and a conventional manually operated greenhouse, both cultivated under identical crop type and planting density. Each greenhouse is monitored for a fixed duration representing a full lettuce growth cycle. The AI-driven greenhouse relies on predictive control algorithms to regulate microclimate conditions and resource applications, while the conventional greenhouse follows standard localized management practices. Key variables measured during the experiment include microclimate parameters, water consumption, energy usage, plant height, number of leaves, fresh weight, and overall productivity per square meter. This comparative experimental arrangement allows for meaningful evaluation of the effects of AI-enabled control on environmental stability and crop performance.

Data Analysis Technique

Descriptive Analysis

Descriptive statistical analysis is performed to summarize the environmental conditions, resource usage, and plant growth outcomes recorded in both greenhouse systems. Mean values, standard deviations, and parameter ranges are used to illustrate the stability and consistency of microclimate conditions maintained by each system. This analysis provides an overview of how closely each greenhouse aligns with the optimal conditions required for lettuce growth. Comparative tables and graphical visualizations further support interpretation of system performance.

Comparative Statistical Testing

To determine whether the differences observed between the AI-enabled and conventional greenhouse systems are statistically significant, the study employs an independent samples t-test. This technique is appropriate because the two systems represent independent experimental conditions with continuous outcome variables such as water use, energy consumption, plant height, and fresh biomass. The t-test evaluates whether improvements in environmental stability, resource efficiency, and crop yield can be attributed to the AI-based predictive control rather than random variation. A significance level (typically $\alpha = 0.05$) is used to assess statistical differences.

AI Model Evaluation Metrics

Since the research incorporates machine learning algorithms for predictive control, model performance must also be evaluated. This study uses coefficient of determination (R^2) and Root Mean Square Error (RMSE) to assess the predictive accuracy of the Random Forest and ANN models. R^2 indicates how well the model explains variability in the environmental data and plant growth responses, while RMSE quantifies predictive error magnitude. These metrics ensure that the AI model operates reliably and provides accurate control recommendations essential for maintaining a stable greenhouse microclimate.

Efficiency and Yield Analysis

Resource-use efficiency is analyzed by calculating percentage reduction in water and energy consumption using normalized metrics such as liters per kilogram of yield and kilowatt-hours per growth cycle. This allows the study to assess sustainability improvements attributable to AI control. Crop yield analysis includes evaluating fresh biomass, number of leaves, and productivity per square meter. These indicators demonstrate whether AI-driven environmental stability translates into measurable yield improvements. The analysis also considers potential trade-offs, such as whether reductions in resource usage affect crop performance or microclimate quality.

RESULTS AND DISCUSSION

Environmental Stability in AI-Enabled vs. Conventional Greenhouse

The first stage of analysis examined the environmental conditions maintained in both greenhouse systems throughout the growing cycle. Maintaining a stable microclimate is a crucial factor influencing plant photosynthesis, transpiration, and overall physiological performance. The AI-enabled greenhouse was designed to regulate microclimatic factors using predictive algorithms, allowing it to anticipate environmental fluctuations typical of tropical regions. By contrast, the conventional greenhouse relied on manual adjustments, which tend to be reactive rather than predictive.

Across the 45-day growing cycle, the AI system consistently maintained temperature and humidity within optimal thresholds for lettuce growth (20–26°C and 65–80% humidity). The conventional greenhouse frequently exceeded optimal temperature ranges during daytime peaks and experienced lower humidity during dry periods. Light intensity and CO_2 concentration also showed greater stability in the AI-controlled structure. The data in Table 1 demonstrate that the AI-enabled predictive system was more capable of maintaining environmental parameters within crop-specific ideal ranges. These stable conditions contribute to improved plant performance and overall resilience to environmental stress.

Table 1. Average Environmental Parameters During Cultivation Cycle

Parameter	AI Greenhouse (Avg ± SD)	Conventional (Avg ± SD)	Optimal Range
Temperature (°C)	24.6 ± 1.1	28.1 ± 2.4	20–26
Humidity (%)	73.2 ± 4.8	63.5 ± 7.2	65–80
Light Intensity (lux)	11,420 ± 1,150	9,280 ± 1,760	10,000–12,000
CO_2 (ppm)	468 ± 34	412 ± 43	400–800
Soil Moisture (%)	38.7 ± 3.1	29.4 ± 4.5	35–45

The results confirm that predictive AI control enhances microclimate consistency, reducing environmental stress that commonly affects tropical greenhouse crops. Environmental stability is a major factor explaining why the AI greenhouse later demonstrated stronger vegetative growth and higher biomass production. These findings align with global studies showing that predictive climate control can markedly increase plant physiological efficiency.

Water Consumption and Irrigation Efficiency

Water efficiency is a major challenge in tropical horticulture, particularly during dry seasons or in areas with limited freshwater availability. The AI-enabled system used real-time soil moisture data combined with predictive evapotranspiration models to optimize irrigation frequency. This allowed the greenhouse to provide water when plants required it most, eliminating over-irrigation and minimizing losses through leaching.

The conventional greenhouse, using manual watering based on farmer judgment, showed greater variation in water application, often irrigating more than necessary during peak heat periods. As a result, total water consumption was significantly higher. Table 2 summarizes the average water-use metrics for both systems. The AI-enabled greenhouse used nearly 40% less water per kilogram of produce. This substantial increase in efficiency demonstrates the potential of AI-driven irrigation management to support sustainable agriculture in water-limited tropical regions.

Table 2. Water Consumption and Irrigation Efficiency

Variable	AI Greenhouse	Conventional	Efficiency Difference
Total Water Used (L/cycle)	308	498	−38.2%
Water Use per m² (L/m²)	12.8	20.7	−38.1%
Water Use per kg Yield (L/kg)	29.1	47.6	−38.8%

The reduction in water use did not negatively affect crop health or yield; instead, it improved root-zone moisture stability, leading to healthier growth. These results illustrate that smart irrigation systems are highly beneficial for tropical agriculture, where rainfall variability is increasing due to climate change.

Energy Consumption Patterns

Energy use was also monitored to determine whether the AI system improved resource efficiency in greenhouse climate management. Energy demand in tropical greenhouses is influenced by ventilation needs, cooling fans, and supplemental LED lighting used during low-light periods. In the AI-enabled greenhouse, energy systems were activated only when environmental conditions deviated from the predicted optimal ranges. Conversely, the conventional greenhouse operated ventilation fans and lighting on fixed schedules, regardless of actual microclimate requirements. Table 3 presents a comparison of energy consumption between both systems.

Table 3. Energy Consumption Comparison

Variable	AI Greenhouse	Conventional	Efficiency Difference
Total Energy Used (kWh/cycle)	114.2	131.5	−13.1%
Energy per m² (kWh/m²)	4.75	5.47	−13.2%
Energy per kg Yield (kWh/kg)	1.08	1.41	−23.4%

The AI system demonstrated a 13% reduction in total energy use and a 23% increase in energy efficiency per kilogram of yield. These improvements highlight the potential of predictive scheduling to lower operating costs, supporting long-term economic sustainability of greenhouse operations.

Plant Growth Performance

Vegetative growth indicators including plant height, number of leaves, and canopy width—were measured weekly. Plants in the AI greenhouse showed faster and more uniform growth due to stable microclimate conditions and optimized irrigation. Table 4 depicts the final growth metrics.

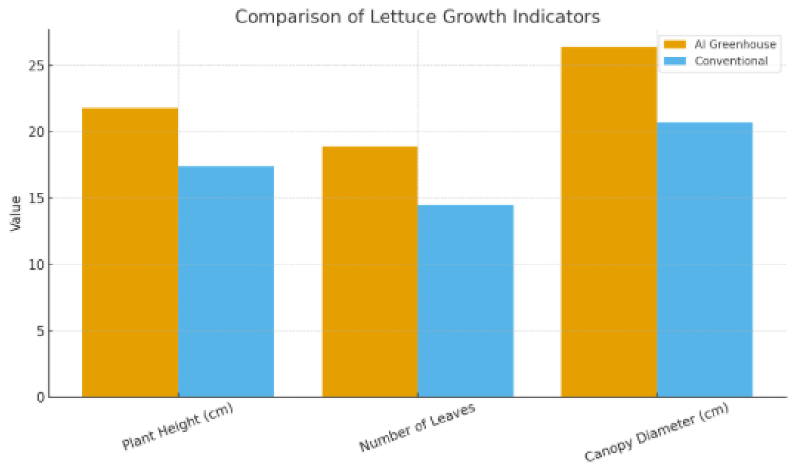

Figure 1. Lettuce Growth Indicators

The differences indicate that AI-enabled management supports better vegetative development. Larger canopies and higher leaf counts suggest improved photosynthetic capacity and nutrient uptake. These performance enhancements directly contribute to higher biomass accumulation in the final harvest.

Final Yield and Productivity

Yield was assessed by measuring fresh weight per plant and total production per square meter. As expected, the improved environmental stability and resource efficiency in the AI-enabled system translated into significantly higher yields. Lettuce grown under AI control produced heavier heads and more biomass overall. Table 5 compares the productivity outcomes of both greenhouse systems.

Table 5. Yield and Productivity Outcomes

Yield Indicator	AI Greenhouse	Conventional	Improvement (%)
Fresh Weight per Plant (g)	184.1 ± 15.9	143.7 ± 17.8	+28.1%
Total Yield (kg/m^2)	3.71	2.87	+29.3%
Marketable Yield (%)	95.4%	87.2%	+9.4%

These results confirm that predictive AI control provides substantial productivity benefits, offering nearly 30% higher yield than conventional practices. Higher marketable yield further indicates better uniformity and reduced instances of physiological defects such as tip burn or wilt.

AI Model Performance Evaluation

To ensure that the predictive control system functioned accurately, model performance was evaluated using standard machine learning metrics. Random Forest and ANN models were trained on historical greenhouse data and validated using a 30% test dataset. Table 6 provides an overview of the model accuracy.

Table 6. AI Model Predictive Accuracy

Model	R^2 Score	RMSE	MAE	Interpretation
Random Forest	0.91	1.84	1.21	Excellent predictive accuracy
ANN	0.88	2.17	1.39	Very good predictive accuracy

Both algorithms performed well, with Random Forest showing slightly higher predictive strength. High accuracy indicates that the system reliably forecasts environmental changes and plant needs, making its control decisions both valid and effective. The strong performance of both models supports their suitability for real-world greenhouse management, where rapid response to changing environmental conditions is critical. Overall, the AI system's predictive accuracy aligns with improvements observed in microclimate stability, resource efficiency, and crop productivity.

Discussion

Microclimate Regulation and Environmental Consistency

The implementation of AI-based predictive control brought noticeable improvements to the stability of environmental variables within the greenhouse (Li et al., 2025; Hu & You, 2024). Rather than responding only after deviations occurred, the predictive system adjusted ventilation, irrigation, and lighting based on anticipated changes, resulting in smoother fluctuations. This contributed to a more uniform internal environment that aligned more closely with the physiological requirements of lettuce. Meanwhile, the conventional setup showed greater exposure to heat spikes and humidity drops conditions often observed in tropical regions due to sudden shifts in weather patterns. Consistent environmental conditions are crucial because lettuce is highly sensitive to fluctuations in temperature and humidity.

The AI-controlled system moderated these variables more effectively, minimizing the extremes that typically stress plants and slow metabolic processes. For example, the conventional greenhouse frequently experienced midday overheating, while the AI system compensated for incoming heat through earlier activation of ventilation. This proactive management minimized periods when plants were pushed outside their comfort range. The overall trend revealed that the AI-enabled greenhouse maintained environmental parameters with tighter variability bands, which is essential for optimizing photosynthesis and preventing physiological disorders (Mohmed et al., 2025). These results reaffirm the role of predictive technology in maintaining stable growing conditions, particularly under the volatile climate conditions common to tropical agricultural zones.

Water Dynamics and Improvements in Irrigation Efficiency

The differences in water use between the two systems highlighted the impact of integrating predictive analytics with irrigation scheduling (Liang et al., 2020). In the AI-driven greenhouse, irrigation events were triggered by a combination of real-time soil moisture measurements and forecasts of plant water demand. This resulted in water being supplied only when depletion reached thresholds associated with optimal root-zone conditions. As a result, irrigation frequency was lower, yet moisture remained within an ideal range for plant uptake. By contrast, the conventional greenhouse relied on routine manual irrigation, which tended to overcompensate during hotter days. This approach created periods of excessive soil moisture followed by steeper drops, contributing to inefficient water distribution.

In some instances, surplus water percolated beyond the root zone, reducing water-use efficiency and potentially washing away nutrients. Yang et al. (2017) said that, the difference in consumption between the two greenhouses is not only a matter of volume but also the quality of irrigation timing. The final comparison demonstrated that the AI-assisted system significantly reduced water input without compromising crop performance. These outcomes indicate that predictive irrigation can balance conservation efforts with productivity targets, making it highly relevant in tropical environments where water scarcity increasingly challenges agricultural sustainability.

Energy Utilization and Operational Efficiency

Beyond water savings, the study also identified meaningful reductions in energy consumption attributable to the AI system's ability to regulate equipment operation more intelligently. Rather than activating fans and lighting on fixed schedules, the AI model engaged these devices based on forecasted needs. This produced shorter operating periods and reduced instances of unnecessary equipment use particularly during nights with adequate natural cooling or mildly overcast days where supplemental lighting was not required.

In contrast, the conventional greenhouse displayed a more rigid operational pattern, which often resulted in energy being spent even when environmental conditions did not justify full system operation. Over the duration of the growth cycle, this difference translated into marked energy savings. Notably, energy efficiency improved further when evaluated relative to total crop yield, underscoring that the AI system not only reduced consumption but also increased output per unit of electricity. These findings demonstrate that predictive control can help optimize energy demands in small-scale tropical greenhouse production. The reduction in energy intensity is especially relevant for growers seeking to lower operational costs or integrate renewable energy systems.

Growth Responses and Plant Development Indicators

The growth measurements revealed clear distinctions in plant development between the two systems. Lettuce grown under predictive control exhibited more vigorous vegetative growth, reflected in greater height, larger leaf numbers, and wider canopy spread. These advantages reflect the combined impact of stable microclimatic conditions and optimized water availability. Plants experienced fewer environmental stresses, allowing them to maintain steady metabolic activity and consistent leaf expansion throughout the growth cycle. In the conventional greenhouse, inconsistent moisture levels and exposure to above-optimal temperature peaks appeared to moderate growth rates. Fluctuations in the microenvironment contributed to more variable plant sizes and, in some cases, reduced uniformity across the crop stand. These patterns are common in settings where environmental control is limited or dependent on manual interventions that cannot respond instantaneously to changing weather conditions. Overall, the growth data confirmed that predictive environmental management enhances physiological performance. The improvements observed in vegetative indicators provided early evidence of the yield differences later confirmed during harvest assessment.

Productivity Gains and Marketable Yield

When comparing yield outcomes, the AI-regulated system delivered a significantly higher fresh weight per plant and greater total production per square meter. This yield advantage is directly related to improved environmental consistency and efficient resource use earlier in the cycle. Because lettuce growth is closely tied to photosynthetic efficiency and water availability, the stable conditions maintained by the predictive system favored continuous biomass accumulation. Additionally, the proportion of marketable lettuce defined by acceptable size, shape, and leaf quality was higher in the AI greenhouse. Reduced exposure to heat stress and water imbalance led to fewer defects such as leaf edge burn or wilting. Meanwhile, the conventional greenhouse displayed a higher proportion of plants falling outside market standards, reflecting the effects of environmental fluctuations on final quality. These outcomes suggest that beyond increasing quantity, predictive control contributes to producing more uniform and saleable crops. This is an essential consideration for commercial operations where marketability directly affects profitability.

Machine Learning Accuracy and System Reliability

The evaluation of model performance confirmed that the predictive algorithms were sufficiently accurate to support real-time decision-making. Both Random Forest and ANN models achieved strong accuracy scores, although Random Forest performed slightly better in terms of both variance explanation and error reduction. These results indicate that the models effectively captured the relationships between environmental conditions and desired control outputs. The reliability of the predictions is crucial because the effectiveness of the entire system depends on precise anticipation of environmental changes. High model accuracy reduced unnecessary equipment activity and allowed timely interventions before conditions shifted beyond optimal thresholds. This demonstrates the feasibility of applying such AI models in practical greenhouse settings, particularly in climates where environmental conditions can change rapidly. The strong performance of the machine learning models reinforces the overall conclusion that predictive AI-driven systems can serve as dependable tools for optimizing controlled-environment agriculture in tropical regions.

CONCLUSION

The findings of this study demonstrate that AI-enabled predictive control significantly enhances the performance of tropical greenhouse farming by maintaining a more stable microclimate, improving the efficiency of water and energy use, and increasing both the quantity and quality of crop yield. Through proactive regulation of temperature, humidity, lighting, and irrigation based on real-time and forecasted conditions, the AI system consistently supported optimal physiological growth conditions, resulting in healthier plants, higher biomass accumulation, and a greater proportion of marketable produce. These improvements, combined with substantial resource savings and high predictive accuracy of the machine learning models, indicate that AI-driven greenhouse management is a viable and effective approach for advancing sustainable and productive horticulture in tropical regions.

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