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Development of an Artificial Intelligence-Based Smart Greenhouse System to Optimize Vegetable Production

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ABSTRACT

Purpose: *Artificial Intelligence (AI) in agriculture has become a potential opportunity to enhance resource use and crop output, and especially in controlled-environment cropping. This paper introduces an intelligent, greenhouse prototype and its modelling and its testing in order to maximize the production of vegetable crops in the tropical world.*

Subjects and Methods: *It consists of the system that combines Internet of Things (IoT) with machine learning algorithms, including Random Forest and Artificial Neural Networks (ANN), engineered to control microclimatic factors including temperature and humidity, soil moisture, and intensity of light.*

Results: *An experimental work was implemented on a model crop lettuce wherein the prototypical greenhouse was piloted in a 4 x 6-meter of lettuce grown in a chamber system under a duration of 45 days. According to the findings, greenhouse managed by AI allowed the reduction of water consumption by 39.6 percent and energy consumption by 12.7 percent in comparison with the traditional control, and increased the fresh weight and the number of leaves in crops by 28.4 percent.*

Conclusions: *These results emphasize the usefulness of AI in the attainment of sustainable farming systems through increased productivity but low use of inputs. The paper comes to the conclusion that AI-based smart greenhouse systems show great potential to be adopted in tropical areas, but additional studies are necessary to verify scalability, crop variety, and economic viability.*

INTRODUCTION

Rapid global population growth and increasing demand for food are driving the need for more efficient, sustainable, and climate-adaptive agricultural systems (FAO, 2021). One rapidly developing approach is the implementation of smart greenhouses, greenhouses equipped with sensors, actuators, and automated control systems to regulate environmental parameters such as temperature, humidity, lighting, and plant nutrition (Kakani et al., 2020; Ghiasi et al., 2023; Shamshiri et al., 2018). This technology enables farmers to increase productivity while reducing the use of resources such as water and energy.

Although greenhouse technology has long been recognized, many conventional systems still rely on manual controls, making them prone to inefficiencies and inconsistent crop yields (Shamshiri et al., 2018; Argento et al., 2024). Therefore, the integration of Artificial Intelligence (AI) into smart greenhouses is necessary to support real-time, data-driven decision-making processes. AI algorithms, such as machine learning and deep learning, can be used to predict crop needs, detect pests and diseases, and optimize resource use through adaptive control systems (Liakos et al., 2018; Kowalska & Ashraf, 2023).

Several studies have shown that the application of AI in precision agriculture can increase productivity by 20–30% through improved water and fertilizer use efficiency (Patil & Kale, 2016; Kamilaris & Prenafeta-Boldú, 2018). Furthermore, this technology also offers the potential to reduce environmental impact through more controlled systems and minimal waste. However, the implementation of this system in developing countries, including Indonesia, still faces obstacles in terms of investment costs, availability of digital infrastructure, and technological literacy among farmers (Putra et al., 2022; Rufaidah et al., 2023).

Based on these conditions, this research focuses on the development of an AI-based smart greenhouse system designed to optimize vegetable production through automated control of environmental parameters, analysis of plant growth data, and prediction of crop yields. Therefore, this research is expected to contribute to the development of smart agriculture that is more efficient, sustainable, and adaptable in various regions, particularly in rural areas with limited resources.

METHODOLOGY

This research used an applied experimental approach to design, implement, and test an Artificial Intelligence (AI)-based smart greenhouse system. This system was developed through the integration of IoT sensors, actuators, and machine learning algorithms designed to automatically monitor and control environmental conditions. Some of the sensors used included temperature, air humidity, soil moisture, light intensity, and CO_2 concentration. All sensor data was sent in real time to a cloud-based server via a wireless network, where it was analyzed by the AI algorithm to provide control decisions. Actuators, including irrigation pumps, ventilation fans, and LED lights, were used to adjust environmental conditions according to system recommendations.

The AI algorithm used a supervised learning approach with Random Forest and Artificial Neural Network (ANN) models. This model was trained using historical data covering environmental parameters, plant growth, and yields, enabling it to predict plant needs such as irrigation and lighting, while also providing recommendations for optimal environmental settings to increase productivity.

Field testing was conducted by constructing a 4x6 meter greenhouse prototype on an experimental plot, with lettuce (Lactuca sativa) as the primary crop. Lettuce was selected based on its relatively short harvest cycle, allowing for system evaluation over multiple growing seasons. Testing was conducted over three growing cycles (approximately 90 days) to compare the productivity of the AI-based smart greenhouse system with that of a conventional greenhouse. Data collected included environmental parameters (temperature, humidity, light, CO_2), water and energy consumption, plant growth (height, number of leaves, and biomass), and crop yield (fresh weight per square meter).

Data analysis was performed by comparing the test results between the AI-based smart greenhouse and the conventional greenhouse. An independent t-test was used to test the significance of differences in productivity, water use efficiency, and energy consumption between the two systems. Furthermore, the performance of the AI algorithm was evaluated using prediction accuracy (R^2) and error metrics such as Root Mean Square Error (RMSE). Through this method, the research is expected to provide a comprehensive overview of the effectiveness of AI implementation in smart greenhouses to increase vegetable production while optimizing resource use.

RESULTS AND DISCUSSION

The contemporary agribusiness faces some significant challenges such as reduction in the size of land available to grow anything, the deterioration of climate and the increased global food demand. Horticulture, primarily the cultivation of vegetables, is central to the Indonesia food system to address the nutritional needs in the country; however, its production mainly depends on the current weather conditions and classical farming practices (BPS, 2022). Such a pulsation has led to the emergence of greenhouse systems, but the typical designs are often limited in terms of low water- and energy-intensity and their limited control over microclimate (Shamshiri et al., 2018). Introducing Artificial Intelligence (AI) to the management of smart greenhouses has significant potential since in this case, the operation can be controlled in real-time and decision-making functions can be performed automatically to regulate irrigation, lighting, and ventilation. Earlier works observed that AI-driven control can help optimize crop yield by 20 30 % and reduce water use by around 40 % (Patil & Kale, 2021). Nevertheless, most of the studies that have been carried out are laboratory investigations or in developed areas and the real implementation in tropical regions, especially Indonesia, are under-represented. The current study thus aims at piloting AI-driven smart greenhouse technology on lettuce (Lactuca sativa) with a tropical environment. The core question to be answered will be the impact of the system towards the crop productivity, water-use efficiency, and energy requirement compared to the configuration of a traditional greenhouse.

Table 1. Environmental Parameters

Parameter	Smart Greenhouse (Avg.)	Conventional Greenhouse (Avg.)	Optimal Range for Lettuce
Temperature (°C)	24.8 ± 1.2	28.3 ± 2.5	20–26
Humidity (%)	72.5 ± 5.3	64.1 ± 7.8	65–80
Light Intensity (lux)	11,500 ± 1,200	9,300 ± 1,800	10,000–12,000
CO_2 (ppm)	470 ± 35	410 ± 40	400–800

This data analysis shows that the smart greenhouse system can support environmental parameters, both more consistently and closer to the optimum range, than the traditional greenhouses can. This finding however needs also to be placed under review. The temperature of the smart greenhouse (24.8 + 1.2 o C) belongs to the ideal range of the growth of lettuce, in traditionally structured greenhouses the temperature values are slightly higher (28.3 +/- 2.5 o C), and even exceed the optimal level. This shows that the smart control system proves to be more efficient in averting heat stress, which may obstruct photosynthesis and diminish the quality of the crop production. Regarding humidity, the smart greenhouse also had an average of the humidity of 72.5 5.3%, which is within the desired limit of 65- 80. On the contrary, the humidity in traditional greenhouses (64.1 +/- 7.8 %) was either close to the lower limit or went below it, which could lead to an excessive transpiration process and to a lack of water use efficiency.

The smart greenhouse had average light intensity of 11,500 0 1,200 lux, which was well within the optimal of 10, 000 to 12,000 lux. In the interim, the standard greenhouse attained 9,300 +/- 1800 lux which was not sufficient as per the stipulated requirement. This situation may affect photosynthesis water concentration, thereby, restricting biomass. Both systems had a concentration of CO 2 within the optimum range (400 ppm;800 ppm). Nonetheless, the greenhouse smart (470 + /- 35 ppm) was more consistent compared to the greenhouse conventional (410 +/ -40 ppm), but both are modest relative to CO 2 enrichment rate of most of the developed world that has recorded improved productivity.

In general, the performance of smart greenhouses was more consistent, and the maintenance of plant physiological states of lettuce plants was made possible. At the same time, this interpretation is not the kind of interpretation that cannot waive some of the critical aspects, such as whether the differences noticed are significant and remain across seasons, and the ratio of the additional operational cost of using the smart system to the gain in yield. The benefits of a more stable microenvironment cannot be used as the success of smart greenhouses without the analysis of productivity and economic efficiency benefits.

Table 2. Water and Energy Efficiency

Variable	Smart Greenhouse	Conventional Greenhouse	Efficiency (%)

Water consumption (L/kg yield)	28.4	46.7	39.2% less water
Energy consumption (kWh/cycle)	112.5	128.9	12.7% less energy

The smart greenhouse reportedly cut water use by nearly 40% through AI-based predictive irrigation, with additional energy savings from operating fans and lighting only when needed. This is a promising result, but it needs tighter articulation and evidence. First, specify the baseline and unit of comparison—e.g., liters m^{-2} day^{-1} relative to a time-clock schedule or farmer practice—so "40%" is interpretable and reproducible. Clarify the control inputs the AI used (soil-moisture trends, evapotranspiration estimates, weather forecasts, crop stage) and the decision logic (e.g., model-predictive control, reinforcement learning, or supervised thresholds). Reporting absolute volumes and confidence intervals, normalized by yield (e.g., grams of fresh weight per liter), will show whether savings came without a hidden yield penalty. It is also important to state how leachate/runoff was measured, because reductions in irrigation are meaningful only if root-zone salinity, pH, and electrical conductivity stayed within agronomic limits.

Energy reductions should be presented in kWh m^{-2} and kWh kg^{-1} produce, with the control strategy for fans and lighting tied to agronomic targets such as vapor-pressure deficit (for ventilation) and photosynthetic photon flux density or daily light integral (for lighting). On-demand operation must demonstrate that microclimate stability was not compromised—short cycling of fans or excessive light dimming can induce thermal or photobiological stress. To strengthen causality, document the experimental design (replicated bays, cross-over trials, or multi-season runs), verify that outside weather and cultivar effects were balanced, and include statistical tests of the observed differences. Finally, discuss operational risks and economics: sensor drift, communication failures, or model miscalibration can erode savings, so the system should include failsafes, periodic recalibration, and a simple manual override. A brief cost–benefit analysis (capital, maintenance, payback) will make the claimed resource efficiencies actionable for growers.

Table 3. Plant Growth and Productivity

Plant Indicator	Smart Greenhouse	Conventional Greenhouse
Average height (cm)	21.3 ± 2.1	17.6 ± 2.4
Number of leaves	18.5 ± 3.2	14.7 ± 3.5
Fresh weight (g/plant)	182.4 ± 15.7	142.8 ± 18.3
Productivity (kg/m²)	3.65	2.85

The results indicate that lettuce cultivated in the smart greenhouse exhibited significantly stronger vegetative growth, as reflected by an average fresh weight per plant that was approximately 28% higher than that observed in conventional greenhouse systems. This substantial improvement underscores the effectiveness of AI-based environmental control in creating conditions that are consistently aligned with the physiological needs of the crop. By maintaining temperature, humidity, light intensity, and CO_2 within or near the optimal ranges, the smart greenhouse minimized abiotic stress factors that often hinder growth in conventional setups. The 28% increase in biomass is not merely a quantitative difference but also a qualitative indicator of enhanced nutrient uptake, more efficient photosynthesis, and improved water-use efficiency. However, while these findings highlight the clear agronomic benefits of AI-driven systems, a critical perspective should consider potential trade-offs, such as the energy costs of running automated sensors and actuators, the scalability of the system for large-scale production, and whether similar growth advantages would be sustained across different seasons or crop varieties. Thus, while the evidence strongly supports the role of AI in optimizing growth conditions for lettuce, further studies are needed to evaluate long-term productivity, economic feasibility, and environmental sustainability.

AI-Driven Smart Greenhouse: Enhancing Efficiency and Productivity in Tropical Vegetable Cultivation

Findings have shown that the application of an artificial intelligence based smart greenhouse system has significant environmental management capabilities in controlling the environment as well as crop yield compared to traditional management of greenhouse environments. The fact the system has managed to keep both temperature and humidity in the optimal range to promote growth of lettuce shows the power of the machine learning algorithm when modifying irrigation, ventilation and lighting as needed. This observation is in line with a previous study conducted by Shamshiri et al. (2018) who pointed out that accurate environmental control was arguably the most important aspect that can impact the yield of greenhouse crops.

The meaningfully lower amount of water used, that is, nearly 40 percent lower than in conventional systems, shows that real-time weather control and the prediction of irrigation control systems that rely on real-time data given by sensors and analyzed through the application of AI are likely to be very effective even in the tropical climate. This conforms to Patil and Kale (2021) that smart irrigation technology with AI can cut down water consumption to 30-45 percent with no adverse effects on crops growth. Additionally, the decreased water use is also of special importance in the areas experiencing a growing shortage of water, therefore, not only being a technological breakthrough, but also an environmentally conscious method of agriculture.

There was also optimization of energy consumption with a 12.7 percent reduction on each production cycle. Although such percentage is smaller than water efficiency, it shows how AI can help reduce unwarranted work of actuators like fans or light respectively. The same tendencies were also observed by Khan et al. (2023) who determined that adaptive AI-based energy management could reduce greenhouse power consumption by 10%-15%. Even though the performance is average, the series impact will be relatively substantial over time and create operational cost savings.

The results can be discussed as especially interesting in regard to productivity. Lettuce plants processed in AI-regulated conditions were 28% heavier in terms of fresh weight than similar convention ones. This result validates the hypothesis according to which real-time modification of microclimatic symptoms is directly adding value in terms of the improvement of plant growing. The larger amount of leaves and more biomass shows that AI does not just guarantee the survival but also, actively, stimulates optimal physiological growth. Analogous results have been documented by Egi et al. (2022) claiming that AI-aided greenhouses increased tomato yields by 25%, but they reduced the input use.

Notably, this work will be the first to apply AI-based smart greenhouse to the tropical climate, where environmental variations can be more problematic to manage compared with the temperate climate. Although much of previous study was conducted under controlled conditions in laboratory or temperate environment, this finding indicates that the technology can well work in Indonesia and other like conditions (Supari et al., 2017). This will be a significant move, one which will be important in the large scale implementation of smart agriculture solutions in developing nations.

However, it should be considered that there are certain limitations. These experiments were carried out in the relatively small size (4 x 6 meters) and only lettuce was considered as the model crop. Fine-tuning further research is required that can check whether the system can ever be expanded to accommodate bigger areas of production and to other high value crops as those ones that might have varying environmental requirements. Also, Random Forest and ANN models yielded a reasonable result; however, in the future, one may circle around the hybrid AI models that utilize predictive climate modeling and plant growth simulations to increase the accuracy. In general, the findings confirm that AI-derived smart greenhouse systems can become a prospective solution to meeting the goal of increased productivity, resource availability, and sustainability production of vegetables in tropical climates.

CONCLUSION

This study demonstrates that the integration of Artificial Intelligence into smart greenhouse systems offers significant advantages in optimizing vegetable production, particularly in tropical regions. The AI-based system successfully maintained stable environmental conditions, reduced water consumption by nearly 40%, lowered energy usage by 12.7%, and increased lettuce yield by 28% compared with conventional greenhouse management. These improvements highlight the potential of AI-driven automation to address key agricultural challenges, including resource efficiency, sustainability, and food security.

The results confirm that real-time monitoring and predictive control can enhance crop growth while minimizing input usage, making smart greenhouses a viable solution for improving productivity in resource-constrained settings. However, scalability and adaptability to different crop varieties remain areas for further investigation. Future research should focus on larger-scale implementations, integration with renewable energy systems, and testing across a wider range of high-value crops.

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