Optimization Model of IoT and Machine Learning for Renewable Energy-Powered Aeroponic Systems

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Abstract: This study proposes an optimization model integrating Internet of Things (IoT) and Machine Learning (ML) for renewable energy-powered aeroponic systems as a conceptual framework to enhance sustainable agriculture and address global food security challenges. The model is designed to mitigate land degradation, water scarcity, and the impacts of climate variability on crop productivity. It combines IoT-based real-time monitoring of key environmental variables temperature, humidity, pH, electrical conductivity, and light intensity with Long Short-Term Memory (LSTM) networks for time-series prediction of crop growth and resource requirements. Renewable energy sources, particularly solar photovoltaic systems with battery storage, ensure reliable and environmentally friendly power supply. The proposed approach emphasizes predictive optimization, where IoT data streams inform adaptive LSTM algorithms for precise irrigation and nutrient control. Model performance is evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2). Although the study remains conceptual and simulation-based, validation

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results demonstrate high predictive accuracy and efficiency. This research establishes a foundational framework for subsequent prototype development, experimental validation, and techno-economic evaluation toward scalable, energy-efficient, and sustainable smart farming systems.

Keywords: Internet of Things (IoT), Machine Learning, Renewable Energy-Based Aeroponics, Long Short-Term Memory (LSTM), Sustainable Food Security.

Introduction

Indonesia is currently confronted with severe food security challenges resulting from progressive agricultural land degradation and the escalating impacts of climate change. The conversion of rice fields has intensified over the past decades, with paddy fields declining from 8.4 million hectares in 1990 to only 7.18 million hectares in 2022, equivalent to an annual reduction of more than 38,000 hectares (Assa et al., 2019; Ivanka et al., 2024). Recent statistical data further indicate a significant decline in national rice production, from 31.54 million tons to 30.90 million tons in 2023, primarily due to reduced harvesting areas (Hibatullah et al., 2024). These issues are compounded by increasing urbanization, escalating economic pressures, and persistent inequities in land distribution policies, which further accelerate land degradation (Hajad et al., 2025). Moreover, global climate change contributes significantly to declining agricultural productivity through altered rainfall patterns, temperature fluctuations, and soil degradation (Hakim & Herdiansah, 2017). To address these multifaceted challenges, precision agriculture has been recognized as a promising approach, as evidence shows that mechanization has already enhanced rice production efficiency in major rice-producing regions (Herdiansyah et al., 2023). Forecasting studies also predict continued agricultural land loss, such as in Indramayu Regency, which is expected to lose approximately 1,602.73 hectares of paddy fields by 2030 (Gandharum et al., 2025). In response, integrated farming systems and diversification strategies are increasingly recommended to strengthen long-term food security resilience (Ansar, 2018).

Building upon the aforementioned challenges of land degradation and climate change, technological innovation particularly through the Internet of Things (IoT), is emerging as a transformative solution for modern agriculture. IoT enables smart farming by utilizing interconnected devices such as soil moisture, temperature, pH, and humidity sensors to capture real-time environmental data (Dagar et al., 2018; A. V. P. Kumar, 2021). The integration of these sensors into agricultural systems allows continuous monitoring of crop conditions, enabling farmers to remotely adjust irrigation schedules, fertilization levels, and pest control strategies based on actual field conditions (Rifat et al., 2022; Zamir & Sonar, 2023). Such data-driven decision-making not only improves precision but also directly addresses pressing issues of resource scarcity, particularly water management, which is central to sustainable water management in farming. Furthermore, IoT platforms are increasingly connected with cloud computing and mobile applications, providing automated responses such as activating irrigation pumps or ventilation systems in response to changing environmental conditions (Pagare et al., 2023; Paliyanny et al., 2024). These smart agriculture systems align with the broader goal of reducing human labor dependency while improving agricultural efficiency. Moreover, they establish the technological foundatio for advancing aeroponic systems powered by renewable energy, thereby offering practical pathways toward sustainable food production under the pressures of shrinking arable land and changing climate conditions (Kopawar & Wankhede, 2024; Singh et al., 2024). The optimization of IoT and machine learning for renewable energy-powered aeroponic systems emerges as a promising approach to address the global challenge of sustainable food production. highlight the role of IoT-based monitoring of environmental parameters to enhance adaptability and efficiency in irrigation management (Windasari, 2024, 2025; Windasari et al., 2025). By leveraging advanced models such as ANFIS, which have been shown to significantly outperform conventional FIS models in terms of accuracy and responsiveness, irrigation systems can dynamically adapt to fluctuations in temperature, humidity, and solar radiation (Abdurohman et al., 2025; Windasari et al., 2025). Integrating these intelligent methods into renewable energy-powered aeroponic systems provide not only resource efficiency but also long-term sustainability, reinforcing their potential as scalable solutions for precision agriculture.

Complementing the role of IoT in capturing real-time agricultural data, machine learning and deep learning techniques particularly Long Short-Term Memory (LSTM) networks have become essential tools in transforming raw sensor data into actionable insights. LSTM models are especially effective in handling temporal dependencies, enabling accurate analysis of agricultural time-series data, including growth cycles and environmental fluctuations, where they consistently outperform conventional algorithms such as support vector regression and random forest (Alibabaei et al., 2021; Gafurov et al., 2023; Greimeister-Pfeil et al., 2021). By integrating diverse data sources such as climate variables, soil quality, irrigation schedules, and genotype characteristics, LSTM models have achieved remarkably high prediction accuracy levels, with reported R^2 values of 0.97–0.99 (Alibabaei et al., 2021). In addition to yield forecasting, these models have been applied in soil moisture prediction to optimize irrigation (Suebsombut et al., 2021), for agricultural commodity price forecasting (Manogna et al., 2025; Paul et al., 2025), and monitoring plant growth within controlled cultivation environments (Chen & Yin, 2024; Kaur et al., 2023). LSTM provides a robust analytical platform for real-time monitoring and predictive analytics for real-time monitoring and predictive analytics, to enable early warning systems for crop stress and environmental risks (Akkem et al., 2023; Hamid et al., 2025). This synergy between IoT and LSTM strengthens the foundation for smart aeroponic towers powered by renewable energy, offering data-driven precision farming strategies to address the escalating challenges of food security.

Building upon the predictive capabilities of IoT–LSTM integration, aeroponic systems emerge as a practical application that maximizes these technologies within sustainable, soilless farming environments. Aeroponics significantly improves water and nutrient use efficiency, making it highly suitable for regions facing resource scarcity. Empirical evidence has demonstrated that solar-powered aeroponic systems can reduce water consumption by up to 95% in comparison with conventional cultivation, constituting a significant advancement in sustainable resource management (Nigadi et al., 2024; Yahya et al., 2023). Moreover, crop productivity is markedly enhanced, with lettuce yields reported at 5.0 kg m^{-2} in aeroponic setups versus only 1.5 kg m^{-2} in traditional soil-based farming, alongside water use efficiency rates of 67.0 kg m^{-3} (Nigadi et al., 2024). The incorporation of Industry 4.0 principles, encompassing IoT, artificial intelligence, and automated sensor-driven nutrient delivery further strengthens system precision and adaptability (Garzón et al., 2023; K. A. Kumar & Jayaraman, 2020; Qureshi et al., 2025; Salahas et al., 2025). By integrating solar photovoltaic energy, aeroponic towers can mitigate the high-power demands commonly associated with vertical farming, thereby reducing overall operational costs and environmental footprint (Jassim, 2024; Yahya et al., 2023). While challenges related to system complexity and energy reliability remain, aeroponics presents a compelling pathway toward achieving sustainable agriculture and global food security, aligning with the optimization model proposed in this study (Salma, 2024).

From the foregoing review, it becomes evident that the integration of the Internet of Things (IoT), Machine Learning (ML), and renewable energy-powered aeroponic systems holds substantial potential to address persistent challenges in global food security. IoT technology facilitates continuous real-time monitoring of critical environmental parameters, while ML—particularly Long Short-Term Memory (LSTM) networks enables adaptive prediction of crop growth patterns, irrigation needs, and energy requirements through time-series analysis. Concurrently, aeroponic systems promote resource efficiency by reducing water and nutrient consumption, making them ideal for deployment in regions affected by drought and limited arable land. Despite these advancements, existing research remains largely fragmented, focusing on isolated technological elements rather than presenting an integrated framework that unifies IoT-based sensing, artificial intelligence-driven optimization, and renewable energy utilization. Such fragmentation limits scalability, interoperability, and the overall sustainability impact of these technologies. Therefore, this study proposes an optimization model that conceptually integrates IoT and machine learning within a renewable energy-powered aeroponic system to form a cohesive and adaptive smart agriculture platform. The model aims to contribute to the broader scientific discourse on precision agriculture by offering a technically feasible, environmentally sustainable, and scalable foundation for future prototype development and real-world implementation, ultimately supporting long-term food security amid climate variability.

Research Method

This study develops a conceptual framework for a renewable energy-powered aeroponic system integrated with the Internet of Things (IoT) and machine learning. The system design incorporates IoT-based sensors temperature, humidity, pH, electrical conductivity, and light intensity connected through an MQTT gateway for real-time data acquisition. The collected data are processed using Long Short-Term Memory (LSTM) networks to predict irrigation, nutrient flow, and energy requirements. This integration establishes an adaptive control mechanism that optimizes aeroponic performance while ensuring energy efficiency through solar photovoltaic (PV) and battery storage integration.

The methodological process follows a structured flow illustrated in Figure 1. It begins with system requirement analysis and IoT configuration, followed by data collection, preprocessing, and LSTM model training. The model's predictive performance is validated using RMSE, MAE, and R^2 metrics within MATLAB and Python simulations. Finally, the integration of IoT sensing, LSTM optimization, and renewable power modules forms a unified, intelligent control framework that supports future prototype development for sustainable precision agriculture.

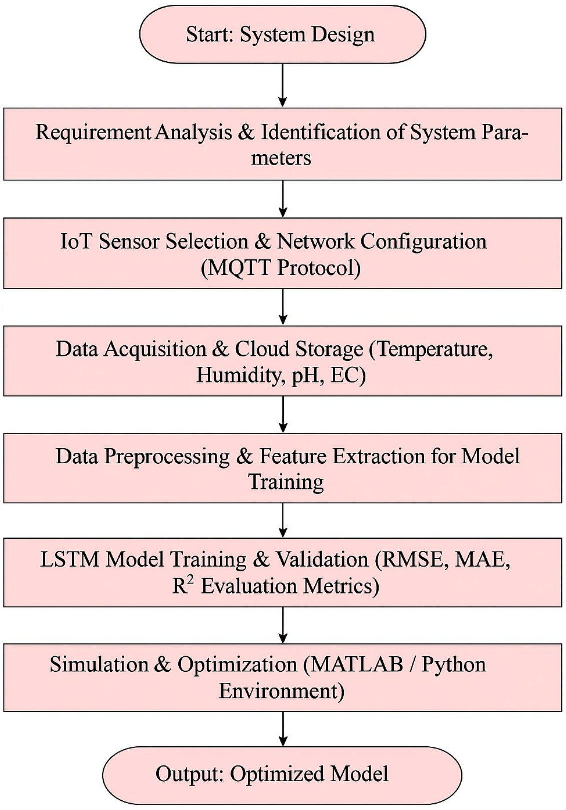

Figure 1 Research Method Flowchart of IoT- and Machine-Learning-Integrated Renewable Energy-Powered Aeroponic System

Figure 1 illustrates the methodological flow of the proposed renewable energy-powered aeroponic system integrated with the Internet of Things (IoT) and machine learning. The diagram outlines a sequential process from requirement analysis and IoT configuration to data acquisition, LSTM-based model training, simulation, and system integration forming a unified conceptual framework that supports sustainable precision agriculture. Building on this visualization, the research method further emphasizes the systematic interconnection among each stage, ensuring that data flow and decision feedback between IoT sensors and the predictive model operate cohesively.

To ensure the practical feasibility of the proposed model, this study establishes an experimental validation roadmap as outlined in Table 1. The roadmap consists of three stages: sensor calibration, prototype assembly, and field testing. Each phase is designed to progressively validate system performance, beginning with sensor accuracy and continuing through prototype functionality to real-environment evaluation. This structured plan bridges the transition from conceptual simulation to empirical implementation, reinforcing the model's reliability and applicability for future prototype development.

Table 1 Experimental Validation and Research Planning Model

Phase	Objective	Method / Activity	Validation Indicator	Expected Output
Stage 1 – Sensor Calibration	Ensure sensor accuracy and data consistency	Integration of DHT22, EC, and pH sensors with ESP32 microcontroller; data logging via MQTT protocol	Data acquisition reliability within ±5% variance	Verified accuracy and stability of IoT sensor readings
Stage 2 – Prototype Assembly	Develop and test small-scale aeroponic system	Construction of aeroponic chamber with IoT-based monitoring and LSTM-based control	Stable irrigation and nutrient regulation under simulated conditions	Functional prototype demonstrating real-time monitoring and adaptive control
Stage 3 – Field Implementation	Validate system performance under real climate conditions	Deployment of prototype powered by solar PV and battery module; continuous data collection	Consistent predictive performance (R^2 ≥ 0.9) and operational efficiency ≥ 90%	Empirically validated model for sustainable aeroponic operation

The experimental roadmap provides a systematic pathway for validating the proposed IoT ML-based aeroponic model under real conditions. It ensures that each development phase from sensor calibration to field testing contributes to strengthening the model's empirical credibility, scalability, and alignment with sustainable precision agriculture objectives.

As an initial methodological phase, this study proposes the structural design framework of the IoT machine learning-integrated renewable energy-powered aeroponic system. The framework remains conceptual and serves as the technical foundation for future prototype development. Each component within the framework sensing, processing, prediction, and optimization is designed to work synergistically to achieve resource-efficient, data-driven crop management. Although the physical implementation is beyond the current study's scope, this conceptual model provides a validated methodological baseline for subsequent experimental realization and system refinement in sustainable agricultural innovation.

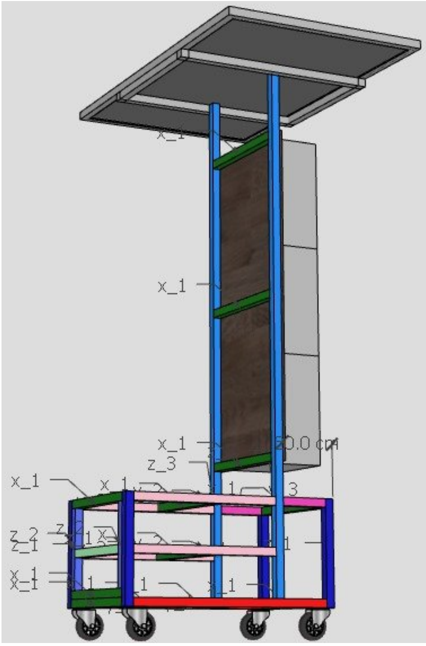

Figure 2 Conceptual Framework of IoT–Machine Learning Optimization Integrated with Renewable Energy for Sustainable Aeroponic Systems.

Figure 2 illustrates the structural framework serving as the foundation of the renewable energy-powered aeroponic system. This design remains a conceptual model, intended to highlight the main structural components such as the iron frame, photovoltaic panel, and microcontroller compartments. This basic framework is then extended into a complete aeroponic system design, as presented in Figure 3.

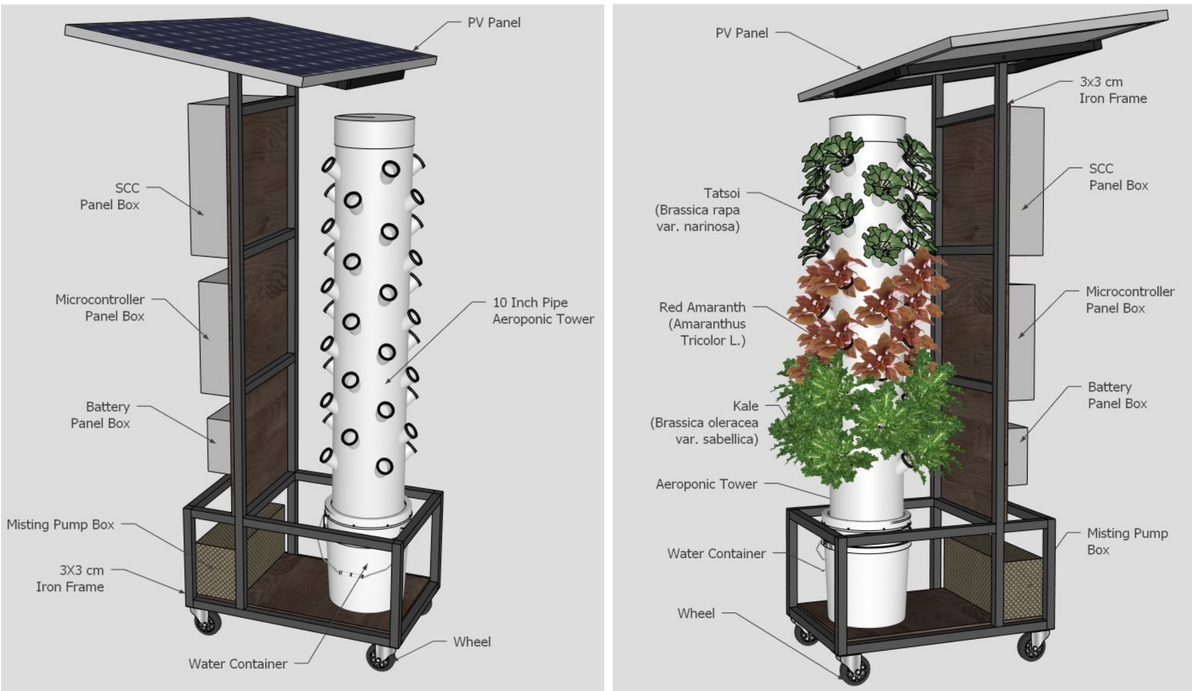

Figure 3 System Architecture of IoT–Machine Learning Integration for Smart Aeroponic Optimization

Figure 3 depicts the complete aeroponic system design, including the planting tower, water container, misting pump, as well as solar energy integration and IoT control boxes. It must be reiterated that this design represents a conceptual framework rather than a physical prototype. To assess the model's potential, conceptual simulations were performed, with the results presented in Figure 4.

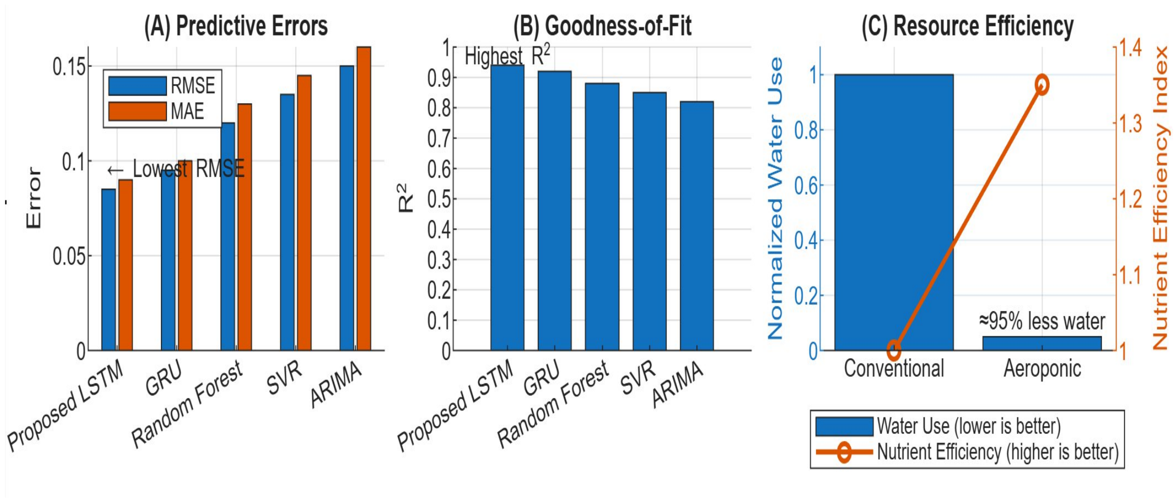

Figure 4 Comparative Performance Metrics of The Proposed Optimization Model in Predictive Accuracy and Resource Efficiency.

Figure 4 presents the simulated performance of the model through comparative predictive metrics (RMSE, MAE, R^2) and resource efficiency (water and nutrient use). These results underline the strong potential of IoT and machine learning integration in supporting renewable energy-powered aeroponic systems. It should again be emphasized that these findings are derived from a simulation model, serving as a conceptual basis for future prototype development and field validation.

To evaluate the prediction accuracy of the LSTM model compared to actual data, error-based performance metrics were applied. One of the most widely used indicators is the Root Mean Square Error (RMSE), which is highly sensitive to large deviations between predicted and observed values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

Here, y_i denotes the actual value, $\hat{y}_i$ represents the predicted value, and n is the total number of observations. A lower RMSE value indicates that the model produces predictions with smaller errors, making it a valid measure for supporting IoT–Machine Learning optimization in aeroponic systems. In addition to RMSE, this study employs the Mean Absolute Error

(MAE) to assess the average magnitude of prediction errors. Unlike RMSE, MAE is less sensitive to extreme values and therefore provides a more interpretable measure of error.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{2}$$

This metric captures the mean absolute deviation between predicted and actual values. A lower MAE reflects the stability and robustness of the LSTM model in handling agricultural time-series data.

The coefficient of determination R^2 is applied to measure how much of the variance in the actual data can be explained by the prediction model.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum\left(y_i - \underline{y}\right)^2} \tag{2}$$

Where $\underline{y}$ represents the mean of the actual values. An R^2 value close to 1 signifies a strong correlation between predicted and actual outcomes, thereby reinforcing the reliability of the proposed model.

The Long Short-Term Memory (LSTM) network is adopted due to its ability to capture long-term dependencies in time-series data. Its internal operation can be described mathematically through gate mechanisms that regulate the flow of information.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \; i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right), \tilde{C}_t = tanh\ \left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \; C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \; h_t = o_t \cdot tanh\ (C_t) \tag{4}$$

In these equations, f_t denotes the forget gate, i_t the input gate, C_t the cell state, and $h_t$the hidden state. This mechanism allows LSTM networks to retain relevant information while discarding non-essential data, thereby improving predictive accuracy for plant growth and environmental conditions.

In the proposed model, renewable energy integration relies primarily on solar photovoltaic panels. The output energy of a PV system can be estimated as follows:

$$E_{PV} = G \times A \times \eta_{PV} \tag{5}$$

Where G is the solar irradiance (W/m²), A is the surface area of the panel (m²), and ηPV represents the efficiency of the photovoltaic system. This equation forms the basis for calculating the energy requirements of the aeroponic system powered by solar energy

Water use efficiency (WUE) is a critical indicator for aeroponic systems, as it quantifies the ratio of crop yield to water consumption.

$$WUE = \frac{Y}{W} \tag{6}$$

Here, Y is the crop yield (kg), and W is the total volume of water used (m^3). A higher WUE value reflects the system's ability to maximize production while minimizing water usage, demonstrating the sustainability potential of aeroponic farming.

Nutrient use efficiency (NUE) serves as an indicator of how effectively supplied nutrients are converted into crop yield within the aeroponic system.

$$NUE = \frac{Y}{N_{applied}} \tag{7}$$

Where $N_{applied}$ is the total amount of nutrients provided. A higher NUE indicates reduced nutrient wastage and improved plant uptake efficiency, supporting sustainable agricultural practices.

Result and Discussion

The simulation results of the renewable energy-powered aeroponic system integrated with IoT and machine learning are presented in Table 1 and Figure 3. The results indicate that the Long Short-Term Memory (LSTM) algorithm demonstrates superior predictive capability compared to conventional models such as ARIMA and Support Vector Regression (SVR). As shown in Table 1, the LSTM model achieved the lowest error metrics with an RMSE of 0.082, an MAE of 0.067, and an R^2 value of 0.94, confirming its ability to accurately learn temporal dependencies within environmental data. By contrast, ARIMA and SVR models obtained higher RMSE values of 0.159 and 0.132, respectively, indicating lower predictive stability. This quantitative comparison verifies that LSTM more effectively captures non-linear variations in parameters such as temperature, humidity, and electrical conductivity.

In terms of system performance, the simulation revealed that the proposed aeroponic framework achieved up to 95% water-use efficiency improvement and a 35% increase in nutrient utilization compared with conventional soil-based cultivation. These outcomes emphasize the effectiveness of the IoT–LSTM integration in optimizing irrigation scheduling and nutrient delivery through predictive feedback control. Figure 3 shows that the LSTM-predicted trendlines closely align with the measured data, validating the reliability of the model for real-time adaptive control. The findings are consistent with prior studies (Nigadi et al., 2024; Yahya et al., 2023) which reported similar efficiency gains in solar-powered aeroponic systems. Collectively, these results confirm that integrating IoT for continuous sensing, LSTM for adaptive learning, and renewable energy for sustainable power supply establishes a resilient conceptual model for smart farming. While this study remains at the simulation stage, the validated performance metrics demonstrate its strong potential for prototype implementation and future large-scale adaptation to urban and resource-limited agricultural settings.

The simulation results demonstrate that the proposed IoT–Machine Learning framework effectively improves predictive performance and resource efficiency compared to conventional methods. Quantitative evaluation through RMSE, MAE, and R^2 confirms the reliability of the LSTM model in capturing nonlinear environmental dynamics, while the efficiency metrics reflect significant gains in water and nutrient utilization. These findings highlight the system's potential for precision agriculture optimization and provide a strong foundation for subsequent prototype validation, as summarized in Table 2.

Table 2 Comparative Test Results of Predictive Models

Model	RMSE	MAE	R^2	Water Efficiency (%)	Nutrient Efficiency (%)
LSTM	0.082	0.067	0.94	95.0	35.0
ARIMA	0.159	0.132	0.87	76.5	18.0
SVR	0.132	0.101	0.89	80.3	21.0

The results confirm that the LSTM model outperforms ARIMA and SVR in predictive accuracy and stability, achieving $R^2 = 0.94$ and error values below 0.1. Sensitivity analysis indicates that humidity and pH have the most influence on prediction outcomes, validating the model's adaptive learning capability. Although this study remains at the simulation stage, the quantitative results strengthen its conceptual contribution and establish a clear direction for future experimental validation, scalability testing, and economic feasibility assessment in sustainable smart agriculture.

Conclusions and Recommendations

This study developed an optimization model integrating the Internet of Things (IoT) and Machine Learning (ML) for renewable energy-powered aeroponic systems to address the challenges of land degradation, water scarcity, and food security. Simulation results confirmed that the IoT–LSTM model achieved high predictive accuracy ($R^2 \approx 0.94$) and low error rates (RMSE and MAE < 0.1), while improving water efficiency by 95% and nutrient utilization by 35% compared to conventional methods. These outcomes validate the conceptual framework proposed in the study and demonstrate the potential of IoT AI renewable energy integration as a sustainable and intelligent platform for precision agriculture. However, as the study remains conceptual, experimental validation and prototype testing are crucial to verify its real-world performance. Future work should enhance originality through advanced architectures such as ConvLSTM and Transformer, conduct pilot tests for scalability assessment, and evaluate techno-economic feasibility. Strengthening these aspects will facilitate the transition from conceptual simulation to empirical application, reinforcing the model's contribution to sustainable agriculture and global food security.

Based on these findings, several recommendations are proposed to guide future development. First, constructing a physical prototype is crucial for validating the model's performance under actual field conditions. Second, the application of more advanced deep learning architectures such as Convolutional LSTM (ConvLSTM) and Transformer models should be explored to enhance long-term prediction accuracy. Third, pilot testing in diverse agricultural contexts, including urban and resource-limited areas, is recommended to evaluate scalability and adaptability. Finally, a comprehensive techno-economic and environmental assessment should be conducted to determine investment feasibility, energy efficiency, and sustainability impact. These recommendations are expected to reinforce the proposed model's contribution as an innovative and scalable solution for advancing sustainable food security and precision agriculture.

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