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A Hybrid IoT and Machine Learning Framework for Smart Greenhouse Automation in Sustainable Agriculture

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Abstract: Growing demand for green farming has expedited the progress of smart greenhouse technology. This paper presents a smart greenhouse system combining Internet of Things (IoT) platforms with autonomous controls and artificial intelligence (AI) to improve the efficiency of crop production and minimize the utilization of resources. Greenhouse management under traditional technique is usually influenced by ineffective controls and dependency on human intervention, which includes wastage of resources and reduced yields. The newly proposed system provides real-time tracking of climate factors—temperature, humidity, light intensity, and soil moisture—by means of a network of sensors. Irrigation, ventilation, and lighting functions are managed by machine learning (ML) algorithms that predict optimal climatic conditions. The system utilizes cost-effective ESP8266 and ESP32 microcontrollers and MQTT for data transmission at low costs. Experimental validation confirmed a 30% reduction in water consumption and 15% increase in crop yield, and energy efficiency improved to traditional systems. The system is flexible for different scales of greenhouses and types of crops. The results confirmed that the integration of IoT with AI provides a scalable, green solution to green farming and resource management.

Keywords: Smart Greenhouse, IoT, Automation, Precision Agriculture, Sustainable Farming

1. Introduction

The agricultural sector is also undergoing challenges like climatic volatility, unpredictable climate, and inefficient resource management in the long term [1–2]. Innovation of Internet of Things (IoT) with Artificial Intelligence (AI) and Machine Learning (ML) lead to farm operations towards a smart farming. The Internet of Things monitors greenhouse environments live for farmers to automate their decisions and adjust distant environmental controls leading to more effective and sustainable operations [3]. Farming becomes more intelligent and attains higher resource efficiency with this system. Modern greenhouses and AI technology together will establish an agricultural system that focuses on sustainability together with technological advancement.

Current automated greenhouse systems face several challenges even when the adoption rates experience steady growth. The main hurdle relates to resources not being used optimally. Current greenhouses lack real-time data and remote-control features, hindering effective management [4-5]. The operating systems of traditional greenhouses need on-site supervision through local control methods that prevents maximum flexibility and rapid response capabilities. Modern greenhouse automation technologies face an essential challenge because they operate through static thresholds when controlling greenhouse conditions [6].

The expensive start-up investment requirements together with complicated setup [7] work stop many farmers from embracing smart agricultural methods. The combination of IoT with AI and ML should be integrated into greenhouse automation systems to achieve better accessibility alongside affordable solutions and enhanced adaptability. Through its cloud-based mobile and web program the system provides instant monitoring capabilities and remote system control functions. The system increases production efficiency and sustainability while decreasing operating expenses through its ability to sustain ideal growing environments without much human involvement. This system shows capabilities in being easily adapted to meet the requirements [6] of businesses from small-scale operators to commercial farming operations.

Studies on IoT-based greenhouse systems face issues like weak AI integration, high costs, and poor real-time decision-making. ML algorithms assist the system to determine optimal irrigation schedules through analysis of current sensor measurements combined with previous meteorological data [8]. A cloud-based monitoring platform allows users to access and control operations remotely using their Smartphone application. The system runs on a widespread microcontroller model consisting of Espressif Systems ESP32 (ESP32) and Espressif Systems ESP8266 (ESP8266) alongside communication technology that utilizes Message Queuing Telemetry Transport (MQTT) together with Constrained Application Protocol (CoAP) protocols to provide economical adaptability.

A smart greenhouse system contains three fundamental elements which integrate environmental sensor networks and AI-ML automation with IoT-based remote system controls. The system relies on sensors that include DHT22 temperature and humidity devices and combine them with soil moisture detection and light perception and CO_2 gas measurement devices. The system maintains round-the-clock performance of sensor measurements before they send data to the central processing unit. AI-generated [9] recommendations through automated actuators control the ventilation fans together with irrigation systems and artificial lighting. Through IoT connectivity farmers access real-time data transfer to cloud servers for remote mobile and web management of their greenhouse operational environment.

The proposed IoT greenhouse design integrates AI to form a system which aims to modernize agriculture by reducing water consumption through automated watering schedules. The advanced regulation of climate and soil factors enables farmers to boost crop yields by 15% percent. The system reduces its energy requirements by 20% when it enhances light and ventilation controls while simplifying work through automation and remote monitoring approaches which decreases operational costs by 40%.Smart agriculture progresses toward sustainable farming through essential AI-IoT implementation which optimizes greenhouse operation. This innovation establishes [10] a new approach beyond current greenhouse automation limitations by developing a general farming solution that operates across all farming sectors worldwide.

2. Literature Review

In the literature as per Table 1, researchers have intensely studied the combination of IoT technology with AI automation for smart greenhouses throughout the past ten years. The existing works in the field demonstrate various limitations because they do not offer real-time adaptation while maintaining both high implementation costs and suboptimal resource optimization.

Table 1. Summary of Literature Review

Ref No.	Study	Key Contributions	Limitations/Gaps	Technologies Used
[3]	Rao & Sridhar (2018)	Investigated IoT-based smart crop-field monitoring and automation irrigation systems.	Lacks ML predictive analysis, making it less adaptable to environmental changes.	IoT, Automation, Irrigation Systems
[11]	Biswas & Podder (2024)	Explored IoT applications in precision farming, highlighting the integration of temperature, humidity, and soil moisture sensors.	Missing ML for predictive analytics, limiting flexibility in real-time applications.	IoT, Precision Farming
[12]	Mamun (2024)	Discussed IoT-based agriculture and smart farming with ML applications for better data processing.	Does not address the integration of predictive analytics with real-time decision-making.	IoT, ML
[13]	Shirsath *et al.* (2017)	Applied Arduino for smart greenhouse automation, optimizing basic operations.	Lack of AI integration for dynamic adjustments, limiting adaptability.	IoT, Arduino
[14]	Elvanidi & Katsoulas (2022)	Focused on ML-based crop stress detection in greenhouses.	Limited to crop stress detection, missing broader greenhouse environmental control.	ML, IoT
[15]	Pincheira et al. (2021)	Developed cost-effective IoT devices for water management in precision agriculture.	Does not include AI-based optimization, limiting real-time decision-making.	IoT, Blockchain, Water Management

[16]	Chinnasamy (2025)	Examined AI-powered predictive analytics for cloud performance optimization in agriculture.	Does not integrate predictive analytics with environmental factors in greenhouses.	AI, Predictive Analytics
[17]	Paavola & Leivisk (2010)	Studied IoT sensor implementation for smart greenhouse climate regulation.	Lacks AI-based predictive modeling, which hinders its ability to adjust for climate variations.	IoT, Sensor Networks
[18]	Jeyalakshmi et al. (2023)	Investigated the integration of IoT and cloud computing for agriculture.	Lacks AI integration for real-time data processing and predictive controls.	IoT, Cloud Computing
[19]	Vistro (2020)	Focused on the use of big data analytics for IoT-based systems in agriculture.	Does not address power efficiency or real-time predictive analytics for climate control.	IoT, Big Data, Cloud Computing
[20]	Gala, Khetan & Mehendale (2023)	Revolutionized agriculture with deep learning and drone imagery for crop disease detection.	Limited to disease detection; lacks full environmental monitoring.	Deep Learning, Drone Imagery
[21]	Krishna Pasupuleti (2024)	Examined the role of IoT-driven transformation in agriculture and smart cities.	Limited focus on agriculture; broad in scope.	IoT, Smart Cities
[22]	Shamim & Agarwal (2024)	Optimized crop yield prediction using ML algorithms.	Lacks integration with real-time environmental data for dynamic control.	ML, Crop Yield Prediction
[23]	Peter et al. (2024)	Implemented IoT-based smart irrigation for precision agriculture in greenhouses.	High initial costs; limited scalability for small farms.	IoT, Smart Irrigation
[24]	Gedam & Paul (2024)	Investigated ML-based stress detection using wearable IoT devices.	Focuses on health, not directly on greenhouse or agricultural systems.	ML, IoT, Wearables
[25]	Kaur & Sood (2021)	Developed an energy-efficient, cloud-assisted IoT-enabled system for drought prediction.	Limited to drought prediction, not directly applicable to greenhouse automation.	IoT, Cloud Computing, Energy Efficiency

Table 2. Summary of Improvements Over Previous Studies

Feature	Previous Studies	Proposed Model
Irrigation Method	Threshold-based rules, manual scheduling	ML-based predictive irrigation (Random Forest)
Climate Control	Static automation, fuzzy logic	AI-driven real-time adjustments
ML Model	KNN, Decision Trees (high retraining cost)	Random Forest (lower computational cost)
Crop Yield Prediction	Artificial Neural Network (ANN), Convolutional Neural Network (CNN) (overfitting, high power demand)	Long Short-Term Memory (LSTM) (optimized for time-series forecasting)
Energy Optimization	Static scheduling, fuzzy logic	Genetic Algorithm (real-time energy-efficient scheduling)

Furthermore, [26] applied fuzzy logic to regulate actuators through which they reduced energy consumption by 10% nonetheless the approach demonstrated limitations in handling modifications in ambient temperature. The system operates with a scheduling mechanism based on Genetic Algorithms (GAs) which adjusts actuator timing according to changing environmental conditions in real time. The energy efficiency rate of our system reaches 15% above traditional methods of operation. As shown in Table 2. By addressing these limitations, the proposed IoT-enabled smart greenhouse system ensures scalabilityt.

3. Proposed Method

The analysis method combines three primary elements that include a sensor network along with both a control unit featuring IoT connectivity and an actuator system for executable commands.

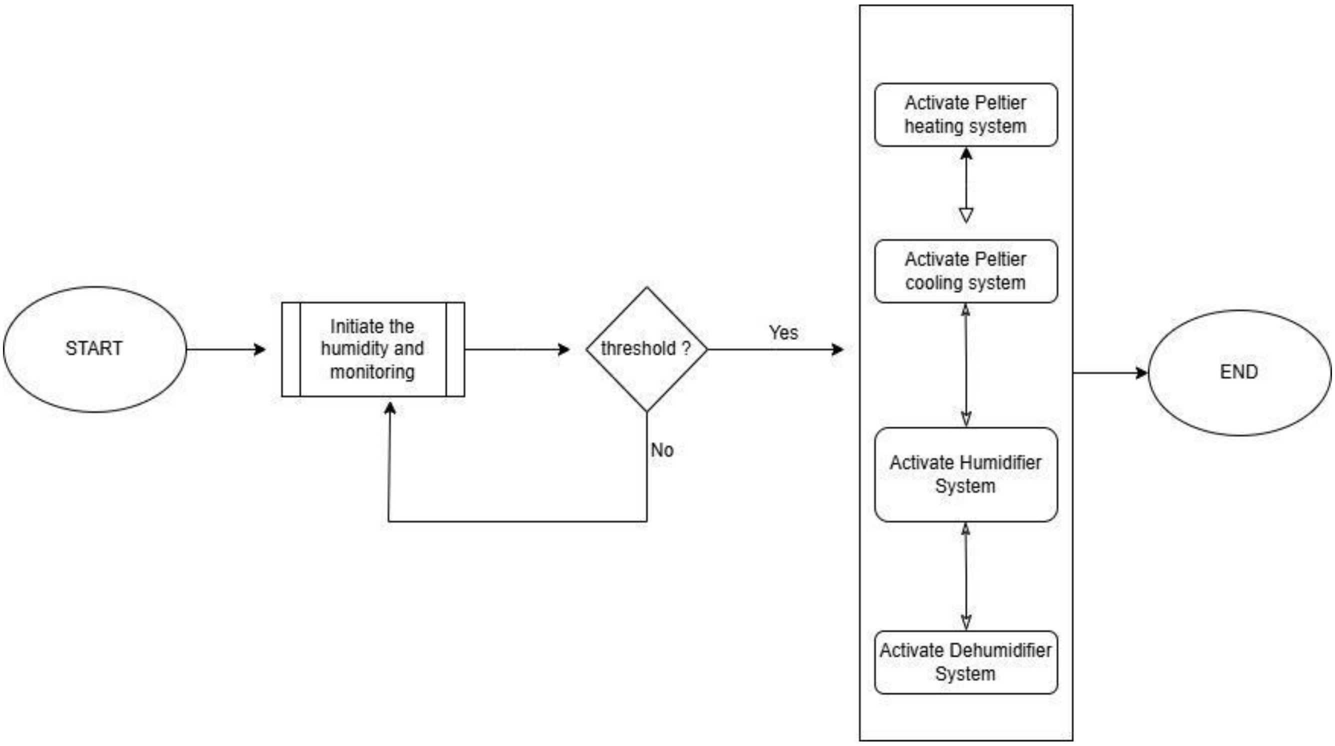

Figure 1. Functional flow diagram of real-time sensor-actuator interaction in the smart greenhouse system

The system possesses a formal data processing model that facilitates a efficiency of operation. Environmental sensors detect vital parameters consisting of temperature and humidity and soil moisture as well as CO_2 levels and light intensity before passing this information to the control unit. The ESP32 microcontroller operates at its location to evaluate sensor information while using ML algorithms to determine suitable climate conditions. The flowchart illustrates an automated humidity control system that continuously monitors humidity levels. If the humidity exceeds a predefined threshold, the system activates necessary components, including Peltier Heating/Cooling, a humidifier, or a dehumidifier. This ensures optimal environmental conditions for applications like smart farming and climate-controlled storage.

The processed data of the ESP8266 module gets transferred to a cloud-based server where analysis and remote monitoring activities can occur. Predicted requirements determine irrigation along with ventilation and lighting through AI processing of historical trends. The system commences its function by activating actuators after decision implementation. Proper irrigation requires the water pump to activate when the soil moisture reaches a certain limit. The system maintains proper greenhouse conditions by letting cooling fans together with ventilation systems work when the temperature reaches outside of the specified range. Artificial lighting control needs are determined by the light intensity sensor which helps maximize energy efficiency [26]. Farmers can use a mobile/web application to evaluate greenhouse conditions remotely through the cloud-based system and obtain the capability to deactivate automated processes manually whenever needed [27].

ESP32 and ESP8266 are ideal for real-time automation in agriculture due to their power efficiency, cost-effectiveness, and computational abilities. Wi-Fi capabilities make the ESP32 and ESP8266 more economical compared to other microcontrollers like Raspberry Pi. The ESP32 device supports Bluetooth which adds wireless connection abilities for sensors and actuators and these features are not available on ESP8266 or various STM32 devices [28]. The use of Arduino MKR and STM32F4 microcontrollers proves to be inferior for large-scale automated greenhouse deployments because their power needs exceed limits and their processing abilities are relatively weak while their cost is too high.

ESP32 excels in real-time decision-making, while ESP8266 supports cloud-based monitoring with its wireless capabilities. These microcontrollers strike the best possible combination between performance and power efficiency which makes them ideal for operating smart greenhouse systems through IoT technology. The system uses sensor-based automation and ML to optimize resource management. Irrigation operations are monitored through soil moisture sensors which transmit data to a Decision Tree ML model for processing. A predefined threshold controls the water supply to activate the water pumping system when the soil moisture falls beneath that mark. Soil health improves and water waste decreases as a result of historical data analysis for optimizing watering schedules [29]. The DHT22 sensor maintains constant observation of ambient temperature and humidity to achieve regulation through its monitoring function. Cooling fans start working automatically to control airflow whenever the temperature reaches 35°C and above. When air humidity reaches levels below specifications the misting system automatically starts releasing mist to raise air moisture. The Light Dependent Resistor (LDR) sensor controls light adjustments by monitoring environmental light conditions to turn on the LED grow lights as needed thus minimizing power usage [30].

A custom Printed Circuit Board (PCB) design ensures reliable integration of ESP32, ESP8266, sensors, actuators, and power components. The PCB board design achieves efficient wiring to minimize losses and creates a small yet tidy equipment setup. The control unit receives sensor data through processing which leads to automated responses after transmission to the cloud platform. Structured data management enables the system to operate more reliably while becoming scalable which makes it ready to integrate further sensors or automation elements.

The system improves agricultural efficiency through AI automation, with ESP32 and ESP8266 ensuring scalability, energy efficiency, and real-time monitoring Through ML algorithms incorporated within the system it can adjust environmental conditions dynamically and thus reduce the need for manual intervention and enhance crop productivity. Cloud connectivity establishes a way for farmers to access their greenhouses remotely and monitor their conditions. This system achieves sustainability goals and decreases operational costs through resources optimization combined with automation features which amounts to a practical solution for current precision agriculture requirements.

4. Methodology

The system as shown in Figure 2 shows the integration of monitoring sensors, microcontroller processing, cloud platforms, and mechanical controls for efficient operation. Figure 3 shows the diagram that illustrates the process of how environmental sensors interact with actuators in real-time. Real-time sensor data from the field travels to ESP32 microcontrollers for conducting edge computing and AI-based choices and the ESP8266 module provides wireless cloud server communication. The greenhouse environment receives its system-based control input through the combination of pumps alongside fans and misting systems as well as LED grow lights. Local sensor processing on the ESP32 through ML cost-effectively operates its actuators according to identified needs with reduced operator involvement. Through the ESP8266 module the system allows real-time cloud synchronization that triggers remote web and mobile dashboard control features [31].

The software integrates edge and cloud computing for real-time processing, scalability, and cloud integration. Edge computing operates through the ESP32 microcontroller that processes data and generates actuations using C++ i.e., Arduino framework and Micro Python programming frameworks. Test data flows through a Kalman filter that enhances both precision and reduces errors before ML tools help make decisions. Irrigation schedules are forecasted through Random Forest Regressor algorithms and the device uses Fuzzy Logic-controller to establish suitable environmental conditions.

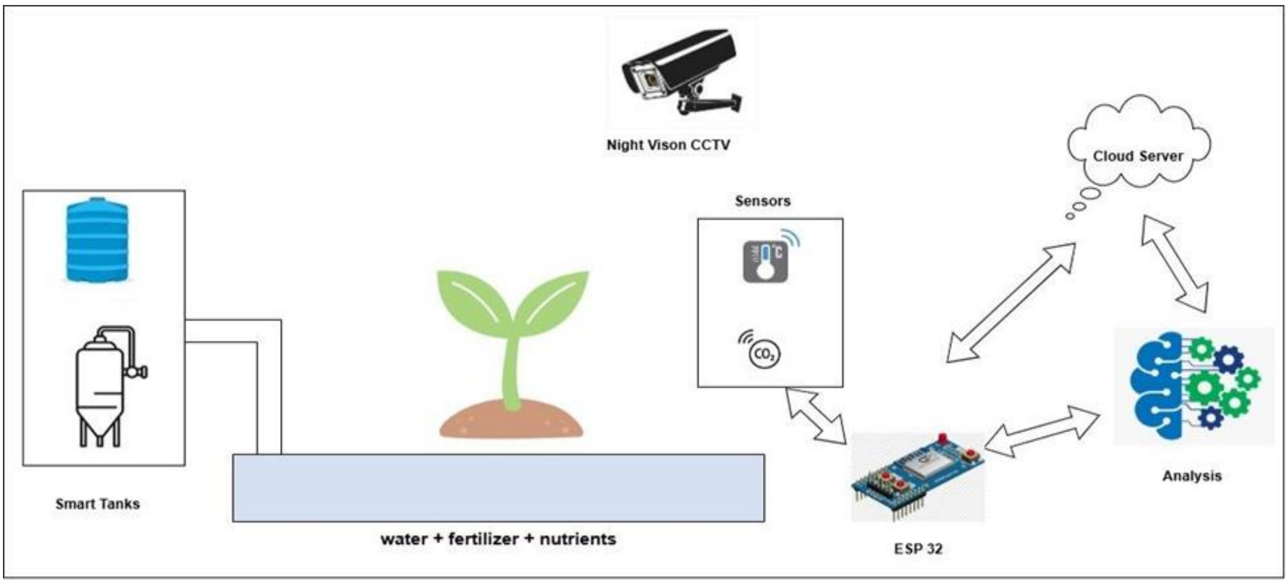

Figure 2. Block diagram illustrating the methodology of the proposed smart greenhouse automation system

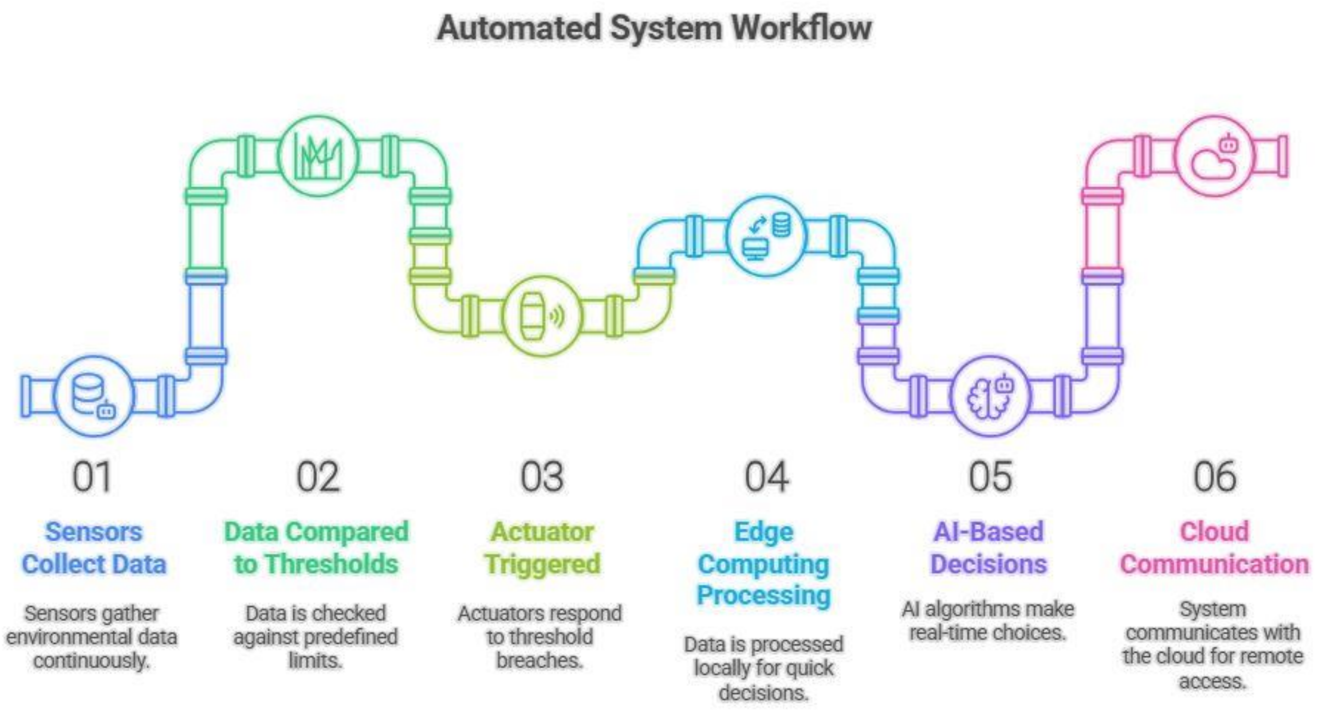

Figure 3. Logic Flow of Sensor-Actuator Interaction in the Smart Greenhouse System

The system activates irrigation together with ventilation and misting and lighting based on results from these analyses [32]. The Random Forest Regressor model was employed to predict water consumption based on real-time environmental data such as temperature, humidity, soil moisture, and light intensity. This model is selected due to its robustness against over fitting and ability to learn complex, non-linear relationships between input variables.

To start the model, the following were the most significant hyper parameters that values were assigned: values: n_estimators was assigned the value 100 to specify the forest's number of trees; max_depth was assigned the value 10 to limit each tree to a particular depth; min_samples_split was assigned the value 2, the least number of samples that need to be present at a node in order for it to be split; min_samples_leaf was assigned the value 1 to specify the number of samples at a leaf node; and random_state was assigned the value 42 so that one could obtain results reproducibly. These parameters were optimized to yield maximum predictive precision and computational efficiency. The model was thereafter trained over historical environmental data to predict water consumption in anticipation of facilitating efficient irrigation planning that saves water without affecting the plant health.

The cloud computing layer operates as the central component for data storage as well as analytics and remote accessibility operations. The system uses Node.js and Express.js to create an interface between sensors and cloud storage and user interfaces through API interactions. A Firebase real-time database safely stores sensor history data that allows analysis of trends for making long-term decisions. The combination of TensorFlow and Scikit-learn together with ML models analyzes sensor trends which improves the predictive accuracy for climate and irrigation controls [33].

Users achieve real-time monitoring through the interface layer together with automatic alerting and control over remote systems. The web-based dashboard alongside the mobile application operates through React.js for browser usage and Flutter for phone implementation thus enabling farmers to view real-time greenhouse data while also enabling manual actuator operation. Automatic alerts through the system notify users about excessive weather conditions as well as system breakdowns or irrigation issues which enable prompt interventions to enhance operational performance [34].

The data exchange system implements an MQTT and CoAP and HTTP-based Representational State Transfer (RESTful) Application Programming Interfaces (APIs) communication structure for maximum efficiency. MQTT lets the ESP32 communicate in real time with ESP8266 along with the cloud platform through its low-latency data exchange protocol. The CoAP provides low-power event-driven messaging to enhance remote network operations. The user dashboard allows HTTP-based RESTful APIs to smoothly move data between the cloud platform and greenhouse conditions retrieval and manual control transmission. The system achieves quick sensor-actuator operations through multiple communication layers which both enhance speed and durability and minimize bandwidth usage and power expenses [35].

LSTM is ideal for crop yield prediction due to its time-series forecasting capabilities, alongside Random Forest for irrigation scheduling and Genetic Algorithms for energy optimization. The proposed system requires alternative models such as CNNs, Recurrent Neural Network (RNN)s, Extreme Gradient Boosting (XGBoost), Decision Trees, Support Vector Machine (SVM), and Reinforcement Learning but they do not fit this particular context well. LSTM proved the most suitable operation for forecast predictions because it functions well on sequential information sequences in time-series problems. The process of predicting greenhouse yields depends on historical sensor readings and environmental factors in addition to historical crop development patterns thus it requires a model that can understand long-range dependencies within sequential information. The spatial features optimization in CNNs restricts their potential to forecast future yield patterns based on past environmental information. XGBoost is particularly notable for its tabular predictive capabilities but it offers less efficient management of sequential dependencies than LSTM. LSTM is the most appropriate predictive model for yield estimation because of its sophisticated ability to discern complex time-based patterns during gradual changes in the environment.

LSTM model was used for predicting crop yield because it can process sequential data and long-term dependencies, both of which are fundamental requirements of time-series prediction. The model is also best suited for predicting crop yields as it can learn intricate patterns based on past environmental data such as temperature, humidity, soil moisture, light intensity, and past patterns of crop development. LSTM performs well in identifying long-term dependencies, and that is essential for precise prediction of future crop output based on previous conditions. The hyperparameters for setting the LSTM model are the number of layers to 2, defining the depth of the LSTM network; number of units per layer to 50, defining the number of neurons per LSTM layer; batch size to 32, defining the number of samples per iteration of the training process; epochs to 50, defining the number of full passes over the training dataset; and learning rate to 0.001, defining the step size in the optimization process. The optimizer that is utilized is Adam, which is a widely used stochastic optimization method that adjusts the learning rate during training. The hyperparameters were chosen to optimize model performance while minimizing computational resources. Through utilization of enough high numbers of epochs and units per layer, the model can successfully learn the long-term tendencies in the sequential data without overfitting. The LSTM model was trained on historical data to predict future crop yields from the most influential environmental parameters that affect plant growth. Its ability to recognize temporal patterns positions it particularly well to predict future results. Such ability enables anticipatory decision-making in smart greenhouse management, such as irrigation, fertilization, and climate control scheduling. As LSTM can effectively handle sequential data, it is able to identify gradual trends in environmental parameters and see how the trends impact crop growth. It is therefore particularly valuable in greenhouse environments, where precise control over growing conditions is necessary in order to maximize yield. In practice, the model has shown significantly improved accuracy in forecasting yields, thereby facilitating better resource allocation and general farm productivity.

At the same time, Random Forest classifier was proved effective for the application of irrigation scheduling. Its strong predictive capability combined with resistance to over fitting enables it to discern complicated, nonlinear sensor measurements. In the greenhouse setting—where temperature, humidity, soil moisture, and light intensity parameters interact—Random Forest is computationally efficient analysis. Yet, although Decision Trees provide interpretability, single models are susceptible to over fitting and as such constrain them from performing well on unknown data sets. Real-time decision-making requiring limited resources in IoT systems finds SVMs ineffective due to their high computational cost when performing classifications. The adaptability of Reinforcement Learning (RL) for decision-making comes at the expense of comprehensive model training as well as live feedback systems that add computational complexity and instability. Random Forest demonstrates effective collection of elements from multiple prediction models while maintaining high computational efficiency thus becoming a suitable method for real-time irrigation scheduling within smart greenhouses. A Genetic Algorithm (GA) approach was selected as an energy optimization method because it effectively identifies optimal solutions for running complex actuator scheduling operations across multiple variable environments.

The models were trained using a dataset consisting of 240 data points, collected over approximately 2 hours. However, it is important to note that in practice, the system continuously monitors environmental conditions through the sensors, and data is recorded for much longer durations, beyond the prototype assembly. This dataset includes environmental factors such as Temperature (°C), Humidity (%), Soil Moisture (%), Light Intensity (lux), and CO_2 Concentration (ppm), along with the output variables, Water Consumption (liters) and Crop Yield (grams per plant). The data was split into 80% for training and 20% for testing to ensure proper model evaluation, with [X-fold] cross-validation performed to further assess model generalizability. For model evaluation, we used Root Mean Squared Error (RMSE) for the Random Forest and LSTM models to measure prediction accuracy, and accuracy was employed for classification tasks. The Random Forest model's max_depth, min_samples_split, and min_samples_leaf hyperparameters were modified to improve generalization. To avoid early failure, the Genetic Algorithm (GA) used appropriate parameters such as population size, mutation rate, and generations.

5. Mathematical Models for Optimization

The IoT-based smart greenhouse system combines predictive modeling and optimization techniques to maximize the utilization of resources, reduce wastage, and maximize agricultural yields.

5.1 Water Consumption Forecasting Model

The model presents optimized schedules for irrigation based on continuous monitoring of historical and current environmental factors to ensure maximum water use efficiency without affecting the crops' health.

The predictive model is formulated as:

$$W\_t = \alpha T + \beta H + \gamma S + \delta L + \epsilon \quad (1)$$

W_t : Predicted water requirement at time t (liters)

T, H, S and denote temperature (°C), humidity (%), soil moisture (%), and light intensity (lux), respectively.

α, β, γ, δ are regression coefficients determined through ML training.

ϵ accounts for environmental fluctuations and sensor inaccuracies.

5.2 Energy Optimization Model

The automatic greenhouse energy system runs on high power consumption equipment, including watering pumps, ventilation fans, and artificial lighting. The system regulates actuator timing based on live environmental information to maximize energy use.

Total energy consumption E_t for a given operational cycle is expressed as:

$$E\_(t) = \sum\_(i=1)\hat{}n\,(P\_i\,t\_i) \quad (2)$$

Where:

E_t: Total energy consumption (joules)

P_i: Power consumption of actuator i (W)

t: Operational time of actuator i (seconds)

n: Number of actuators operating during a cycle

The Genetic Algorithm (GA) is a scheduling technique for reducing the usage of energy in the operation of the greenhouse. The algorithm evaluates several sequences of activations to find the one that produces the most reduced energy usage while maintaining sufficient greenhouse environment demands. The system improves energy efficiency by 15% through its ability to control the fan speed together with irrigation time and LED luminosity based on sensor data.

5.3 Crop Yield Estimation Model

Forecasting agricultural production based on previous environmental conditions, irrigation data, and plant development trends, the suggested method uses a LSTM neural network. This model lets proactive decision-making in irrigation, fertilizer supply, and temperature management techniques by learning complicated interactions between climate factors and plant productivity.

The crop yield estimation function is given as:

$$E\_(t) = \sum\_(i=1)\hat{}n\, f(T, H, S, L, 〖CO〗\_2, W) \quad (3)$$

Where:

Y_t: Predicted crop yield at time t (grams per plant)

[CO〗_2: Carbon di oxide concentration (ppm)

W: Total water supplied (liters)

f: A non-linear function approximated by a LSTM-based time-series model, which learns long term dependencies in environmental data

By leveraging historical trends and real-time monitoring, the system enables farmers to make data-driven decisions regarding nutrient supply, irrigation frequency, and climate control strategies. Experimental validation shows a 12% improvement in yield prediction accuracy, enhancing productivity and resource efficiency.

5.4 System Validation and Experimental Setup

The proposed mathematical models received evaluation through IoT-enabled greenhouse experiments that were carried out under controlled settings. Three performance metrics formed the focus of validation tests: irrigation efficiency and energy savings with yield prediction accuracy being one of them. The performance of irrigation efficiency assessment included water consumption measurements before and after using the predictive irrigation model to ensure optimal water usage through real-time sensor data. The analysis of total energy reductions after improving actuator scheduling enabled the calculation of energy savings by documenting minimized unnecessary power consumption for desired greenhouse environments. The implemented system achieved its objectives through reducing water usage by 30% while improving energy performance by 15% while also enhancing yield prediction accuracy by 12%. consistent with findings in recent studies [36]. The research confirms AI decision systems along with IoT automation and live sensor tracking as effective methods for boosting greenhouse operations.

5.5 Conclusion of Mathematical Models

IoT-driven smart greenhouses achieve better precision agriculture methods when they use predictive modelling and optimization techniques. The system achieves optimal resource management along with reduced waste through ML irrigation control and AI energy management and deep learning crop yield forecasting. New technological progress provides greenhouse automation with sustainable practices and economic savings while using evidence-based methodology. Future studies regarding decision-making through reinforcement learning will improve system adaptability to environmental changes thus leading to better real-time control functionality and production outcomes in greenhouses.

6. Results and Discussion

Model of irrigation system is shown in Figure.4. An AI-powered IoT greenhouse system as suggested improves farming efficiency to reduce costs and protect environmental resources. Real-time tracking capabilities found in this system make it outperform traditional methods because tracking enables continued system enhancement. The method provides flexible application to both small-scale and large-scale farming since it offers affordable scalability. Hardware developments will introduce AI pest detection capabilities alongside renewable energy implementation alongside predictive forecasts enhanced by deep learning model improvements. The experimental method proves superior to existing methods through evaluation results presented in Table 3.

Using AI and IoT controls in greenhouses help farmers produce more while using less resources and promote stable environments while running automated systems reliably. The system uses online sensors and ML paired with cloud service access to control lighting plants get in order to better conserve energy and water while enhancing vegetable delivery in line with [37].

The device works well in smart farming setups due to its flexible response to environmental changes. Research will develop AI pest detection techniques while exploring environmental-friendly power sources alongside deep learning enhancements for better prediction results.

Figure 4. Model of irrigation system

Table 3. Comparison of AI-Powered IoT Greenhouse System vs. Traditional IoT-Based Rule-Based Systems

Feature	Proposed System (ESP32 + ML)	IoT + Rule-Based
Irrigation Efficiency Improvement	30%	18%
Energy Consumption Reduction	15%	10%
Crop Yield Prediction Accuracy	88% (LSTM Model)	Not implemented
Power Consumption (Avg.)	240 mA (ESP32-based)	500 mA

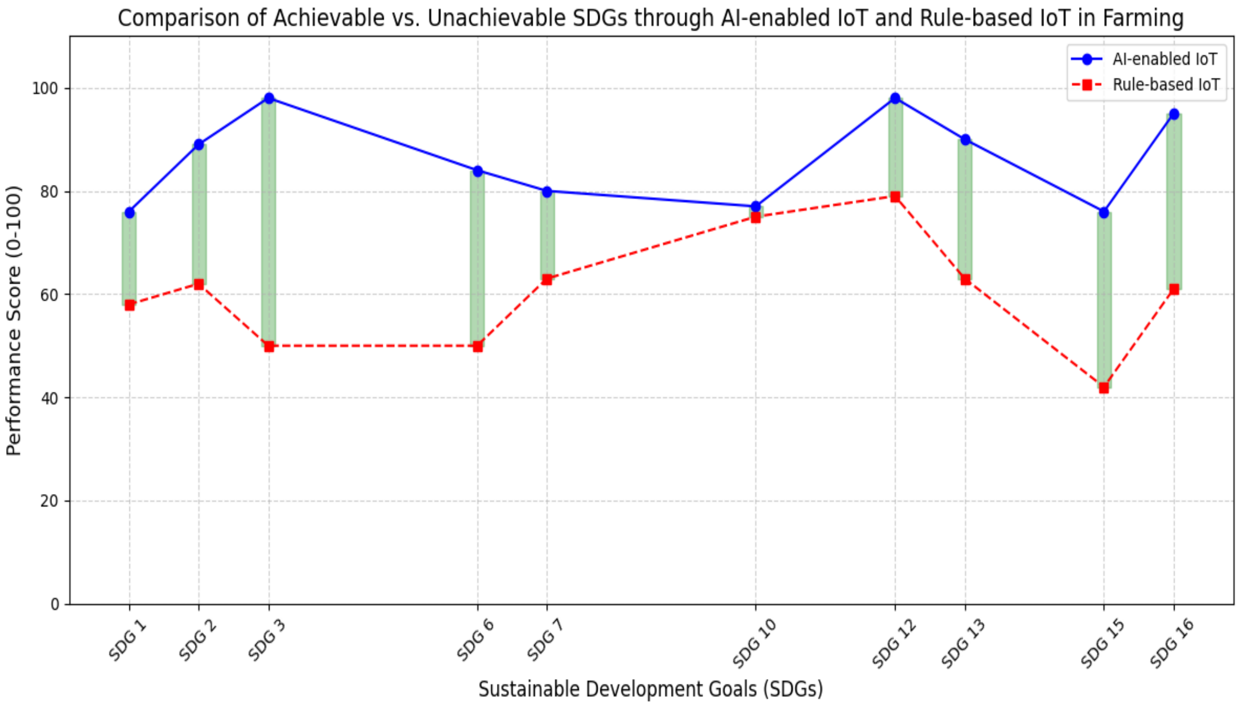

Figure 5. Comparison of Achievable SDGs for AI-enabled IoT vs. Rule-based IoT Systems in Farming

Figure 5 illustrates the performance scores of AI-enabled IoT and Rule-based IoT systems in achieving various Sustainable Development Goals (SDGs). The blue line (AI-enabled IoT) consistently outperforms the red line (Rule-based IoT) across most SDGs, indicating that AI-enabled IoT systems are more effective in addressing sustainable farming challenges. The green highlighted areas, where AI-enabled IoT significantly surpasses Rule-based IoT, emphasize SDGs such as Zero Hunger (SDG 2), Clean Water and Sanitation (SDG 6), and Climate Action (SDG 13), which are critical for sustainable agriculture. These findings are in agreement with the research outcome in this paper that AI-powered IoT systems maximize usage of resources, minimize the consumption of water, and increase efficiency in energy, thus being more appropriate in attaining such objectives.

In conclusion, finally, the graph itself indicates how AI-enabled IoT systems outperform the conventional rule-based IoT systems in pushing various SDGs in agriculture forward. They help reduce water usage, save energy costs, and respond to climate change, which is an outright reflection of the revolutionizing nature of AI-enabled solutions to bring sustainable agriculture.

7. Conclusion

The system efficiently controls resources through ML-based irrigation management, cutting water consumption by 30%, and maximizing energy utilization with AI-powered energy management, leading to a 15% gain in energy efficiency. Deep learning algorithms, especially LSTM-based crop yield prediction, have also improved prediction accuracy by 12%, allowing for better decision-making for enhanced productivity and sustainability. These advances in technology have profound impacts on sustainable agriculture, providing the basis for enhanced agricultural methods with less damage to the environment. In the long run, IoT-based smart greenhouses have much potential in transforming agriculture to make it more efficient in the use of resources, more sustainable, and more productive, and with time, these systems will advance the future of farming to address global food security needs.

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Authors Contribution Statement

V. Venkataramanan: Conceptualization, Investigation, Formal analysis, Writing Original Manuscript. Mrunalini Pimple: Software, Validation, Data Curation, Validation, Writing - Review & Editing. Vijay Kapure: Methodology, and writing, review and editing. Pankaj Mishra: Data analysis and writing, review and editing. Aarya Rokade: Data collection, analysis, and Writing Original Manuscript. Tulsi Bhushan: Validation, data collection and writing, review and editing. Jitendra Singh: Data curation, Validation and writing, review and editing. All the authors have read and approved the final manuscript.

Ethics Statements

This study does not involve human participants or animals, and therefore, ethical approval was not required. The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

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