Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Edge computing and IoT technology for enhancing crop yield inside greenhouse conditions

Revanasiddappa Bandi

revanasiddappa@bnmit.in

BNM Institute of Technology

Arvind C.S

Bioinformatics Institute, Agency for Science, Technology and Research (A*STAR)

Suma Swamy

Dr. H N National College of Engineering

Research Article

Keywords: Edge Computing, IoT, Greenhouse Automation, Precision Agriculture, Smart Farming, Raspberry Pi

Posted Date: June 23rd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9992515/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Abstract

Ensuring sustainable agricultural production and addressing global food security challenges require intelligent technologies capable of continuously monitoring and optimizing crop-growing environments. This study presents an integrated Edge Computing and Internet of Things (IoT)-based framework for real-time greenhouse monitoring and crop yield prediction. The proposed system employs a Raspberry Pi 3B+ edge device to acquire and process environmental data from multiple sensors measuring temperature, humidity, light intensity, and soil moisture. By performing data processing at the edge, the system reduces communication latency, enables rapid decision-making, and minimizes dependence on centralized computing resources. The processed data are subsequently transmitted to the ThingSpeak cloud platform for storage, visualization, and analytical purposes. To evaluate the effectiveness of the proposed framework, coriander (*Coriandrum sativum*) was selected as the experimental crop. Environmental and growth data were collected under four cultivation scenarios comprising greenhouse and open-field conditions. Crop yield prediction was performed using four supervised machine learning algorithms: Linear Regression (LR), Random Forest Regression (RFR), Support Vector Regression (SVR), and Multi-Layer Perceptron Regression (MLPR). Experimental results demonstrated that greenhouse cultivation provided more favorable environmental conditions, resulting in improved crop growth and higher yields compared with external environments. Among the evaluated models, Linear Regression achieved the best predictive performance, attaining an R^2 value of 0.93. The findings highlight the potential of combining edge computing, IoT, and machine learning to enable precision agriculture, improve resource utilization, reduce labor dependency, and support sustainable greenhouse farming practices.

Introduction

Agriculture remains the primary source of livelihood for rural populations in India. While several countries have adopted smart farming techniques to boost agricultural productivity, this change is still in its early phases in India. Traditional farming methods, which are labor-intensive and dependent on unpredictable environmental factors, often result in suboptimal crop yields. Farmers largely rely on seasonal rainfall and manual practices, which are not always conducive to consistent agricultural output.

The Internet of Things (IoT)—the concept of connecting physical devices embedded with sensors and communication capabilities—has revolutionized many domains, including agriculture. IoT enables real-time data collection and monitoring of different parameters, including temperature, humidity, soil moisture, and light intensity, thereby supporting informed decision-making. IoT in digital agriculture makes tasks like crop selection and land preparation, to irrigation management and harvesting [1]. Complementary studies also consider factors like soil quality, weather forecasting, fertilizer use, pest control, logistics, and storage.

Smart agriculture is an example of ubiquitous computing [2], where technology becomes seamlessly integrated into daily farming operations. Wireless Sensor Networks (WSNs) and Wireless Sensor and

Actuator Networks (WSANs) are integral to this approach. These networks automate processes and provide real-time updates to farmers through mobile devices, increasing productivity and reducing costs [3].

A viable alternative to conventional farming is greenhouse farming. It involves sensors to monitor internal environmental factors—temperature, humidity, soil moisture, and light intensity—which can be automatically adjusted without manual intervention [4]. Recent studies, such as those by [5], demonstrated how well machine learning models estimate agricultural yields under controlled greenhouse conditions.

The objective of this study is to build an intelligent greenhouse monitoring system that combines Edge Computing and IoT technologies. The system continuously acquires data from multiple sensors and processes the information locally in real time, enabling efficient regulation of environmental conditions required for optimal crop growth. Specifically, coriander (Coriandrum sativum) is used as a test crop due to its sensitivity to environmental factors. Data is analyzed at the edge using a Raspberry Pi 3B + and visualized through the ThingSpeak cloud platform.

Edge Computing minimizes latency by processing data close to the source, enabling faster responses and improved efficiency. While IoT provides rich, continuous data from greenhouse sensors, Edge Computing allows localized processing for immediate action. The synergy between these two technologies offers a robust solution for real-time agricultural monitoring.

Literature Survey

Several research works have been carried out in the past in the field of smart agriculture using IoT technology and machine learning [6]. To create an effective strategy and manage the massive amount of data involved in agricultural output, IoT and web services are utilized [7]. IoT and cloud computing can assist in solving problems for farmers and advance modern agriculture. Controlling and monitoring of humidity inside a greenhouse using an android mobile application was developed [8]. This system uses an Android smartphone that is linked via WiFi to a central server and a humidity sensor to communicate with an Arduino microcontroller. The test results are displayed in the datasheet for the sensor.

In order to improve the homestead field, farmers can consider agricultural characteristics thanks to the role of IoT in modern agriculture [9]. It has been explored how to compare soil moisture, temperature, and humidity in an open field with a greenhouse and ideal soil moisture. Greenhouse values fall between open field and ideal values, according to the findings. The key to increasing agricultural productivity is keeping an eye on the environment [10]. Temperature and humidity in agricultural fields are monitored with the CC3200 chip. In order to obtain the photographs and transmit them via multimedia storage (MMS) to the farmer's mobile device via Wi-Fi, the camera is also interfaced with a chip.

Automatic farming control [11] using global systems for mobile communication (GSM) technology and embedded systems provides an efficient collection of soil moisture, humidity, temperature, etc. and

processes them using a microcontroller that provides instructions to the controlling units, such as the heating element, humidifier, sprinklers, solar shade, exhaust fan, etc. In order to establish a greenhouse and keep the necessary level of parameters. By using this method, farmers can cultivate a variety of crops, irrespective of the location of cultivation and seasons.

Intelligent monitoring and controlling are very much essential in a greenhouse environment [12] where all the sensors are deployed, and the sensed data are transmitted to a central gateway. The gateway nodes send sensor data to agricultural professionals through the internet so that the system gets advantages like uninterrupted monitoring of mobile within the greenhouse, higher yield and fertility, and minor human dependency.

The design of a greenhouse traceability model for seedlings recordkeeping and tracking using IoT [13] uses a web application to control and monitor the greenhouse, and farmers can also utilize the application regarding seedlings information, which is developed inside the greenhouse, so that the usage of water can be minimized. The prediction of millet crop yield was carried out [14] using a radio frequency (RF) classifier and achieved 99.74% accuracy. Different inputs like soil moisture, max temperature, min temperature, humidity, and rainfall have been used for the prediction.

Yield prediction using the linear regression technique has been discussed [15], where the data is generated by using different sensors such as temperature, nitrogen, phosphorous and potassium (NPK), Ph, and humidity from the actual field. This data was analysed and stored in a dedicated system and collected through a server to access the system. To use multiple regression techniques to forecast the production of several crops, including cotton, wheat, and maize, namely interactions, quadratic, pure-quadratic, and polynomials [16]. The optimal regression model is chosen using the metrics root mean squared error (RMSE), mean percentage prediction error (MPPE), and coefficient of determination (R2).

Machine Learning Techniques such as perceptron, multilayer neural network (PMNN), multiple linear regression (MLR), support vector machine, M5-Regression tree, and K-Nearest neighbor [17] examine the predictive accuracy of linear regression versus machine learning algorithms for predicting crop yield for ten crop datasets. The models are validated using a variety of performance indicators, including the correlation factor (R), RMSE, normalized mean absolute error (MAE), and root relative square error (RRSE). The results showed K-nearest neighbor (KNN) and M5- prime produce the lowest average RMSE (5.14 and 4.91), RRSE (79.46% and 79.78%) & MAE error (18.12% and 19.42%), and the highest co-relation factor (0.41 and 0.42) compared with other techniques. So, M5-Prime has been identified as a suitable model for estimating crop yield in agricultural production systems.

Crop prediction system that combines remote sensing data with machine learning techniques [18]. The system gathers information from sensors that monitor pH, temperature, soil moisture, rainfall, and humidity. The collected data are processed using different machine learning algorithms, including Decision Tree, Linear Regression, Gradient Boosting, and Random Forest. The performance of these algorithms was compared, and Gradient Boosting produced more accurate yield prediction results than

the other methods. The study showed that sensor-based data analysis can help farmers select crops that are more suitable for local environmental conditions.

A decision support system for crop recommendation [19] using agrometeorological factors such as temperature, humidity, and rainfall. Several classification algorithms, including K-Nearest Neighbors (KNN), Decision Tree, and Random Forest, were evaluated by adjusting their parameters and comparing their prediction performance. Based on the results, the most effective model was chosen for crop forecasting. The proposed system provides useful information to farmers, enabling them to make better cultivation decisions and improve agricultural productivity. An IoT-based gradient descent approach was used, and different sensors like humidity, temperature, soil moisture, and pH are employed to assess crop conditions collected from different sensors using IoT [20]. In addition to these, additional parameters like land type, soil type, and area sown are considered during the system build. These values are fed to the graphical user interface (GUI) developed for crop prediction and provide recommendations using the crop suggestion UI. A deep neural network (DNN) was used for the prediction of a crop cultivated, production range, and fertilizer used.

Recent advancements in smart agriculture have focused on integrating IoT technologies, sensor networks, and machine learning techniques to improve crop productivity and resource management. An automated drip irrigation system [21] that optimizes water usage by supplying crops with the required amount of water. In this study, soil health card information was used to guide the application of essential nutrients required for crop growth. An ultrasonic sensor was integrated to measure water levels, while supplemental grow lights enhanced the photosynthetic activity of plants. Greenhouse conditions were maintained through temperature monitoring and fogging mechanisms. The sensor readings were periodically transferred to a cloud server, where the data could be accessed by e-commerce and other agricultural stakeholders for analysis and operational planning

A vertical farming monitoring system [22] that continuously collects environmental data through various sensors. A BeagleBone Black controller was used to process the sensor readings and upload them to the ThingSpeak cloud platform. The system also assisted in maintenance management by tracking equipment locations and enabled remote operation of lighting and irrigation through a web-based application. In addition, the system provided graphical representations of sensor data to support effective analysis and decision-making.

The multispectral imaging [23] for monitoring maize growth at different developmental stages. Images were captured using a Mini MCA 6 camera mounted on an unmanned aerial vehicle (UAV), and radiometric calibration was performed through the empirical line calibration technique. The calibrated reflectance values were validated against Handheld-2 measurements, achieving high coefficients of determination (R^2 values ranging from 0.964 to 0.988). The findings demonstrated the effectiveness of machine learning methods in extracting valuable crop-growth information from multispectral imagery.

The contribution of IoT technologies toward addressing climate-related challenges in agriculture was examined [24]. Their work highlighted the role of intelligent sensing, automated control systems, and

data-driven optimization in enhancing agricultural sustainability. Similarly, the barriers and opportunities associated with large-scale IoT deployment in agriculture. Their analysis emphasized applications such as temperature and humidity regulation, frost detection, wildfire prevention, nutrient management in greenhouse cultivation, intelligent shading systems, automated feeding mechanisms, and energy-efficient operations powered by renewable sources. These technological innovations were shown to improve productivity while reducing operational expenses [25].

The integration of IoT and Wireless Sensor Networks (WSNs) for modern agricultural applications [26] was discussed. Their study demonstrated how sensor-generated data could be utilized for monitoring crop health and forecasting weather conditions. A convolutional neural network-based approach was applied for potato blight disease detection, while automated irrigation was triggered based on soil moisture measurements. The proposed framework enabled remote crop supervision and promoted cost-effective farming practices, ultimately supporting higher agricultural productivity.

The emergence of smart greenhouse systems driven by IoT technologies was reviewed [27]. These greenhouses rely on interconnected sensors and communication networks to collect real-time environmental data. Parameters such as temperature, humidity, carbon dioxide concentration, illumination, and ventilation are continuously monitored and controlled. The study emphasized the significant benefits of smart greenhouse technologies in improving cultivation efficiency and resource utilization.

A large-scale automated hydroponic farming system utilizing biodegradable coconut coir as an alternative to conventional rock wool media [28]. The framework supported the cultivation of multiple crops under optimized greenhouse conditions to maximize productivity. Crop growth rates for leafy vegetables were estimated using the K-Nearest Neighbors (KNN) algorithm. Experimental results indicated that the Nutrient Film Technique (NFT) combined with coconut coir provided superior performance, achieving an accuracy of 93%. The classification performance was assessed using F1-scores, yielding 93% for the weighted average and 33% for the macro average.

Crop yield prediction for four major food crops cultivated across 24 regions of Senegal [29]. Their study employed machine learning techniques along with multiple linear regression to assess crop productivity. Three groups of input variables were considered, namely climatic factors, vegetation indices, and a combination of both. The performance of several prediction models, including Support Vector Machines (SVM), Random Forest (RF), Neural Networks (NN), and LASSO Regression, was evaluated. The findings showed that integrating climate data with vegetation indicators resulted in better prediction accuracy. Among the crops studied, peanut yield was predicted with the highest accuracy, mainly because of its strong dependence on climatic conditions.

The application of machine learning methods for crop yield estimation, focusing primarily on the palm oil industry. The authors [30] discussed worldwide palm oil production patterns and examined the datasets, input parameters, and prediction techniques commonly used in yield forecasting studies. Their review highlighted recent developments in crop yield prediction models and their relevance to palm oil

cultivation. In addition, the study outlined the benefits and shortcomings of existing approaches and identified several research issues that require further investigation.

Despite the progress achieved by previous studies, existing systems often face difficulties in effectively monitoring and managing data obtained from multiple sensors. To address this limitation, an IoT-based greenhouse monitoring and control system capable of supervising crop conditions in real time was proposed [31]. The work was driven by the need to overcome the constraints of conventional greenhouse management, where monitoring is largely performed manually and requires considerable effort. Such practices may delay the detection of changes in plant growth and environmental conditions. The proposed framework integrates IoT devices with edge computing technology, enabling sensor data to be processed locally before transmission. This approach supports continuous monitoring, faster data analysis, and timely decision-making, thereby improving greenhouse management efficiency.

To perform sensor data analysis, the proposed system uses four machine learning techniques, such as multi-layer perceptron regression (MLPR), support-vector regression (SVR), random-forest regression (RFR), and linear regression (LR) for predicting the crop yield.

Although prior research has explored machine learning and IoT applications in agriculture, few studies have examined the combined impact of Edge Computing and IoT on crop yield prediction within greenhouse environments. This work contributes to that gap by applying machine learning algorithms—Multi-Layer Perceptron Regression (MLPR), Support Vector Regression (SVR), Random Forest Regression (RFR), and Linear Regression (LR)—to evaluate crop performance across different scenarios.

The developed framework facilitates prompt decision-making and reduces dependence on manual intervention. The automation of agricultural operations helps improve crop production efficiency. Owing to its low implementation cost, scalability, and efficient energy utilization, the system can be adopted in regions with limited resources. Such technologies have the potential to promote the growth of smart agriculture practices in India.

Materials and Methods

A smart agriculture system was designed and implemented using a miniature greenhouse setup to maintain suitable environmental conditions for crop growth. The greenhouse was equipped with sensors to measure important parameters such as temperature, humidity, soil moisture, and light intensity. The sensor readings were collected continuously to monitor changes in the growing environment. Based on the measured values, control actions were carried out automatically. A fan was used to regulate temperature, a water pump supplied irrigation when soil moisture levels decreased, and LED lights provided additional illumination when natural light was insufficient.

The collected data were processed using an edge computing device located near the greenhouse environment. Processing data at the edge reduced the need for continuous communication with remote servers and enabled faster response to environmental variations. This approach supported real-time

monitoring and control of greenhouse conditions while minimizing delays commonly associated with cloud-based processing. The processed data is then transmitted to a cloud platform for visualization, remote monitoring, and further analysis, as depicted in Fig. 1.

The system comprises two main functional components:

i) Data Acquisition and Control:

A network of environmental sensors is deployed within the greenhouse to track real-time conditions. These sensors are connected to an edge device that controls actuators such as fans, lights, and pumps, thereby maintaining optimal plant growth conditions with minimal human intervention.

ii) **Data Analysis and Cloud Integration**:

Collected sensor data is refined and transmitted to a cloud dashboard, enabling visualization, alerts, and historical trend analysis. This facilitates informed decision-making and supports predictive insights related to crop health and yield.

Design and Challenges

Designing an efficient greenhouse monitoring system involves several challenges, particularly in managing real-time environmental data across varying conditions. This study addresses these challenges by building a compact greenhouse prototype integrated with multiple sensors—temperature, light, humidity, soil moisture, and ultrasonic—to ensure accurate and timely data collection.

The strategic placement of sensors is crucial. Incorrect positioning can lead to inaccurate readings, which in turn affect system decisions. For example, the system could malfunction if the light sensor is positioned incorrectly to activate lighting when needed. To ensure precision, sensor data is processed locally using an edge device rather than relying solely on cloud-based computation, which reduces delays and increases reliability.

Real-time sensor data is uploaded to the ThingSpeak [32] cloud for visualization and monitoring. The system was tested under four environmental scenarios—two within the greenhouse and two outside—to evaluate its impact on plant growth and yield. Various performance metrics such as temperature stability, light consistency, and humidity control were assessed to analyze system effectiveness.

In this research, four scenarios have been considered for analyzing the crop prediction. Scenario 1 and 2 for within the greenhouse model and Scenario 3 and 4 for outside the greenhouse model. The different metrics are calculated such as R^2, MSE, and RMSE for all four techniques as shown in Fig. 2.

Hardware Components

The proposed greenhouse system integrates various sensors and modules, each serving a specific purpose in intelligent monitoring and controlling the environment for optimal crop growth. The primary hardware components used are described below:

a) Ambient Temperature and Humidity Sensor (DHT11):

This low-cost digital sensor measures ambient temperature and humidity. It operates between 3.5 V and 5.5 V and provides readings with ± 1°C and ± 1% accuracy. It uses a thermistor and a capacitive humidity sensor to generate values every 2 seconds. The sensor communicates with the controller via a GPIO pin using a pull-up resistor as depicted in Fig. 3a.

b) Light Sensor (BH1750):

This sensor measures light intensity (in lux) and uses the I²C protocol for communication with the Raspberry Pi. It includes two primary pins—SCL and SDA—and operates within 2.4 V to 3.6 V as depicted in Fig. 3b. It helps the system decide when to activate supplemental lighting.

c) Soil Moisture Sensor (LM393):

This sensor detects soil water content using electrical resistance. A comparator (LM393) outputs digital or analog signals depending on the moisture level. It operates between 3.3 V and 5 V and automatically regulates irrigation based on soil moisture levels, as depicted in Fig. 3c.

d) Ultrasonic Sensor (HC-SR04):

This sensor, which uses ultrasonic waves to measure plant height or distance, determines distance by timing the return of the echo. The four pins that it uses are Trigger, VCC, Echo, and GND, as depicted in Fig. 3f.

e) Cooling Fan and Relay Module:

A 4-channel relay module allows control of high-voltage devices like pumps, fans, and lights as depicted in Fig. 3d. The fan (12V, 120mm) is activated when the internal temperature exceeds the threshold, helping maintain a stable climate.

f) Raspberry Pi 3B+:

Serving as the edge computing unit, this board features a 64-bit quad-core processor (1.4 GHz), 1 GB RAM, Wi-Fi, Bluetooth, and multiple GPIO pins as depicted in Fig. 3e. It processes sensor data locally and handles control logic and cloud communication.

Pin Diagram

A pin diagram helps to map sensor connections to the appropriate GPIO pins on the Raspberry Pi 3B+. In this system, each sensor and actuator is connected to a Raspberry Pi to allow for real-time monitoring and control.

Specific GPIO pins are linked to the light sensor (BH1750), ultrasonic sensor (HC-SR04), soil moisture sensor (LM393), and temperature and humidity sensor (DHT11). The relay module is also wired to GPIO outputs to control devices like the cooling fan, water pump, and grow light.

Proper pin allocation ensures stable communication and prevents signal conflicts. The GPIO layout and wiring are visually summarized in Fig. 4, which guides hardware integration and troubleshooting during implementation.

Data Acquisition and Analysis

Coriander (Coriandrum sativum) was selected as the test crop due to its sensitivity to environmental conditions. Data from sensors—including humidity, light intensity, temperature, and soil moisture—was collected over 20 days across four scenarios: two within a controlled greenhouse environment and two outdoors, as shown in Fig. 5.

Inside the greenhouse, sensor data was captured automatically and uploaded to the ThingSpeak cloud using the Raspberry Pi. For outdoor scenarios, Plant height, humidity, and temperature were recorded using a mobile device. while a separate light sensor captured intensity values.

Each dataset includes daily readings in addition to the corresponding crop yield and height. These measurements were visualized using bar graphs to assess how different conditions affected plant growth. The collected data were later used for performance evaluation and crop yield forecasting analytical techniques.

Experimental Setup

The experimental setup involved assembling a miniature greenhouse equipped with essential sensors and actuators. Hardware components used are listed in Table 1, including the Raspberry Pi 3B+, DHT11, BH1750, LM393, HC-SR04, relay module, and a cooling fan. The software stack included Ubuntu OS, Python 3.6, and libraries such as adafruit, smbus, and time. ThingSpeak was used for cloud-based visualization.

Table 2 outlines the control logic: if temperature, humidity, or light values cross predefined thresholds, automated actions such as fan activation, water pumping, or lighting adjustments are triggered.

Table 1
Greenhouse Monitoring and Control Hardware

Components Name	Specifications of the component
Raspberry pi	Raspberry Pi 3B+
Sensors	i) Temperature/Humidity Sensor (DHT 11) (3.5V-5.5V operating voltage; temperature range: 0-50^{o}C; humidity range: 20% to 90%; accuracy: ±1°C and ± 1%) ii) Soil Moisture Sensor (LM393) (3.3V-5V operating voltage; 15mA current) iii) Light Sensor (BH 1750) (2.4V-3.6V operating voltage, 0.12 mA current; 12C bus communication; accuracy: +/- 20%) iv) Ultrasonic Sensor Distance (HC-SR04) (Operating voltage: +5V; Accuracy: 3 mm; Measuring angle covered: <15°C; Operating Current: <15 mA)
Analog to digital converter	ADS 1115
Relay Module	5V Relay modules
Cooling fan	Maximum switching voltage: 150V AC; 24V DC
Power supply and adapter	Input: 120-240V; Output: 5V-12V

Table 2
Threshold Settings for Greenhouse Sensors

Sensors	Threshold value	Generated value	Action taken
Temperature	26^{0}C	22^{0}C	Temperature is normal. Fan OFF
		28^{0}C	Temperature is more Fan ON
Humidity	60%	65%	Humidity increase, Pump ON
		50%	Humidity decrease Pump OFF
Light Sensor	50 lux	70 lux	Brightness is normal light OFF
		49 lux	Brightness is less light ON

Data Refinement

Sensor readings occasionally included noise or false spikes. Temperature readings from the DHT11 were cross-verified against a standard device to eliminate anomalies, as shown in Table 3.

Table 3
Temperature Deviation of the DHT11 Sensor from the Standard Device

Room temperature using a standard device	Temperature reading from the DHT11 sensor	Error in temperature
24.8	24	0.8
24.9	24	0.9
25.3	25	0.3
25.4	25	0.4
25.9	26	-0.1

Greenhouse Miniature Model

The physical setup included precise sensor placement to ensure accurate data collection. For instance, the light sensor was enclosed in plastic fiber to prevent external interference, and the edge device Raspberry Pi enabled multitasking, managing simultaneous data acquisition, control, and cloud communication as depicted in Fig. 6.

Data Visualization

ThingSpeak served as a cloud platform for IoT data analysis for aggregating and displaying real-time sensor data. Channels were configured to display environmental trends using line plots, with data updated every 15 seconds. Communication was handled via Python scripts using the Adafruit DHT library.

Results

The proposed system was evaluated across four distinct scenarios involving coriander crop growth—two within a controlled greenhouse and two in open-field conditions. Each scenario was monitored for 20 days, with daily sensor readings and yield recorded in Table 4.

Table 4
Environmental Conditions and Yield Summary

Scenario	Location	Avg Temp (°C)	Humidity (%)	Light Intensity (lux)	Plant Height (cm)
Scenario 1	Inside Greenhouse	24.4	60.34	215.16	8.12
Scenario 2	Inside Greenhouse	27.5	79.95	115.65	8.66
Scenario 3	Outside Greenhouse	33.95	56.6	8320.3	6.18
Scenario 4	Outside Greenhouse	33.95	56.6	8320.3	6.42

Table 5
Model Performance Summary (LR)

Scenario	R^2	MSE	RMSE
Scenario 1	0.8219	12.25	3.50
Scenario 2	0.9594	4.71	2.17
Scenario 3	0.9770	0.31	0.56
Scenario 4	0.9670	0.53	0.73
Overall	**0.9313**	**4.45**	**1.74**

Visual monitoring was conducted through ThingSpeak, displaying real-time sensor data such as humidity, light intensity, and temperature as shown in Figs. 7 and 8. Automated control actions (e.g., fan, pump, light) responded based on threshold values, ensuring consistent conditions in the greenhouse environment.

Discussion

The results clearly demonstrate that coriander plants grown inside the greenhouse produced significantly higher yields (28–30g) compared to those grown outdoors (12–16g). Indoor conditions also maintained moderate temperatures (24–27°C) and stable humidity (60–80%), which were optimal for crop growth. In contrast, outdoor scenarios experienced higher temperatures (33.95°C) and excessive light intensity (over 8000 lux), leading to lower yield and shorter plant height.

Key observations:

- **Stable temperature and humidity** inside the greenhouse contributed to healthier crop development.
- **Higher plant height** correlated with increased yield (e.g., Scenario 2: 8.66 cm, 28g).

- **Excessive outdoor light and heat** negatively affected growth and reduced yield.
- **Edge computing** allowed for localized data processing, enabling faster, real-time responses to environmental changes and lowering the requirement for manual intervention.

Comparative Study

Four data-driven techniques were evaluated for their ability to predict crop yield. Performance was measured using the coefficient of determination (R^2). The comparison is summarized in Tables 6 & 7.

Among all methods, **Linear Regression** delivered the most consistent and accurate predictions across all scenarios. Its simplicity, interpretability, and robustness make it particularly suitable for structured agricultural data in low-resource environments.

Table 6
Comparative performance of R^2 for four scenarios using MLPR, SVR and RFR

Technique	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Overall R^2
MLPR	0.6287	0.9465	0.1192	0.2066	0.4156
SVR	0.7037	0.4783	0.3305	0.8777	0.5975
RFR	0.3363	0.9306	0.9150	0.6444	0.7065
LR	**0.8219**	**0.9594**	**0.9770**	**0.9670**	**0.9313**

Table 7
Comparative analysis with state-of-the-art methods

Approach	Environment	Best Model	Performance
ML-based yield prediction	Hydroponic greenhouse	SVR	$R^2 \approx 0.88$
ML with hydroponics	Controlled greenhouse	MLP	$R^2 \approx 0.90$
ML yield prediction	Open-field crops	Random Forest	$R^2 \approx 0.86$
Edge-IoT + ML prediction	Smart greenhouse	Linear Regression	**$R^2 = 0.93$**

Conclusion

This study demonstrates the effectiveness of integrating Edge Computing and IoT technologies for monitoring and managing the greenhouse environment in real time to improve crop yield. A smart greenhouse prototype was developed using a range of sensors to measure key environmental parameters, with local processing enabled by a Raspberry Pi 3B + and data visualization through the ThingSpeak cloud platform.

Experimental results across four scenarios showed that crops grown inside the greenhouse under controlled conditions yielded significantly better outcomes than those grown outside. Real-time sensor

feedback and automated environmental control contributed to healthier plant growth, greater efficiency, and reduced dependency on manual labor.

Among the predictive approaches tested, the simple regression-based method consistently delivered the highest accuracy, with an overall R^2 of 0.9313, affirming its suitability for yield estimation in controlled agricultural setups.

The findings highlight that smart farming using Edge-IoT integration is not only feasible but highly beneficial for precision agriculture, particularly in resource-constrained settings. It offers a scalable and low-cost solution to optimize plant health, conserve resources, and ensure sustainable production.

Future work may explore advanced feature selection methods, alternative crops, long-term deployment in real-world greenhouses, and addressing challenges related to data privacy, system maintenance, and scalability.

Declarations

Competing interests

There are no disclosed conflicts of interest for the authors.

Open Access

This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit h t t p : / / c r e a t i v e c o m m o n s. o r g / l i c e n s e s / b y / 4. 0 /.

Funding

This study was conducted without any external financial support from governmental, commercial, or non-profit funding bodies.

Author Contribution

Revanasiddappa Bandi: Conducted the literature survey, developed the methodology, implemented the work, analyzed the results, and prepared the manuscript. Arvind C. S.: Formulated the problem and corrected the manuscript. Suma Swamy: Assisted in manuscript correction.

Acknowledgement

We sincerely appreciate BNM Institute of Technology for giving us the chance to perform the study. Author 2 is currently employed at A*STAR Singapore, and no research was conducted there.

Data Availability

The data supporting the findings of this study are available from the corresponding author and can be shared upon reasonable request.

References

1. Managave A, Savale O (2016) Precision agriculture using Internet of Things and wireless sensor networks. Int J Adv Res Comput Eng Technol, 5(4)
2. Aqeel-ur-Rehman (2015) Smart agriculture: An approach towards better agriculture management. Omics E-Book Group
3. Sreekantha DK, Kavya AM (2017) Agricultural crop monitoring using IoT – A study. Proceedings of the 11th International Conference on Intelligent Systems and Control (ISCO). https://doi.org/10.1109/ISCO.2017.7855968
4. Rahali A, Alami H, Hilali A (2015) Design and implementation of a system for monitoring and remote control of a greenhouse climate parameters. J Autom Control Eng 3(5):425–427. https://doi.org/10.12720/joace.3.5.425-427
5. Mokhtar A, El-Ssawy W (2022) Using machine learning models to predict hydroponically grown lettuce yield. Front Plant Sci 13:706042. https://doi.org/10.3389/fpls.2022.706042
6. Barooah P, Alvi M, Ringler C, Pathak V (2023) Gender, agriculture policies, and climate-smart agriculture in India. Agric Syst 23:100830. https://doi.org/10.1016/j.iot.2023.100830
7. Gayatri MK, Jayasakthi J (2015) Providing smart agricultural solutions to farmers for better yielding using IoT. IEEE Conference on Technological Innovations in ICT for Agriculture and Rural Development. https://doi.org/10.1109/TIAR.2015.7358528
8. Hanggoro A, Putra MA (2013) Greenhouse monitoring and controlling using Android mobile application. International Conference on Quality in Research (QiR). https://doi.org/10.1109/QiR.2013.6632541
9. Veeranjaneyulu M, Reddy DVR (2018) IoT in modern agriculture. International Journal of Engineering Science Invention (IJESI), ICMEEP-18 Special Issue, 18–24

10. Prathibha SR, Hongal A (2017) IoT based monitoring system in smart agriculture. International Conference on Recent Advances in Electronics and Communication Technology. https://doi.org/10.1109/ICRAECT.2017.52
11. Agarwal A, Krishna BV, Kumar NS (2014) Automatic corporate farming control mechanism (using embedded systems and GSM technologies). Int J Eng Res Manage Technol, 1(1)
12. Arshad J, Tariq R, Saleem S, Ur Rehman A, Munir HM, Golilarz NA, Saleem A (2020) Intelligent greenhouse monitoring and control scheme. Indian J Sci Technol 13(27). https://doi.org/10.17485/IJST/v13i27.311
13. González-Amarillo CA, Corrales-Muñoz JC (2018) An IoT-based traceability system for greenhouse seedling crops. IEEE Access 6:67528–67535. https://doi.org/10.1109/ACCESS.2018.2877293
14. Josephine BM, Ramya KR (2020) Crop yield prediction using machine learning. Int J Sci Technol Res, 9(2)
15. Meeradevi, Mundada MR (2020) Automated control system for crop yield prediction using machine learning approach. Int J Appl Eng Res 14(2). https://doi.org/10.35940/ijitee.F3713.049620
16. Shastry A, Sanjay HA (2017) Prediction of crop yield using regression techniques. Int J Soft Comput 12(2). https://doi.org/10.36478/ijscomp.2017.96.102
17. Gonzalez-Sanchez A, Frausto-Solis J (2014) Predictive ability of machine learning methods for massive crop yield prediction. Span J Agricultural Res 12(2). https://doi.org/10.5424/sjar/2014122-4439
18. Tatapudi A, Varma PS (2019) Prediction of crops based on environmental factors using IoT and machine learning algorithms. Int J Innovative Technol Exploring Eng (IJITEE) 9(1). https://doi.org/10.35940/ijitee.A4695.119119
19. Sowmya BJ, Mundada G (2019) Data analytics on agrometeorological parameters for building a utility system for farmer community. Int J Recent Technol Eng (IJRTE) 8(2). https://doi.org/10.35940/ijrte.B2676.078219
20. Priya PK, Yuvaraj N (2019) An IoT based gradient descent approach for precision crop suggestion using MLP. Journal of Physics: Conference Series, 1362, 012038. https://doi.org/10.1088/1742-6596/1362/1/012038
21. Kodali RK, Jain V (2016) IoT based smart greenhouse. IEEE Region 10 Humanitarian Technology Conference (R10-HTC). https://doi.org/10.1109/R10-HTC.2016.7906846
22. Chin YS, Audah L (2017) Vertical farming monitoring system using the Internet of Things (IoT). AIP Conference Proceedings. https://doi.org/10.1063/1.5002039
23. Guo Y, Chen S (2022) Machine learning-based approaches for predicting SPAD values of maize using multi-spectral images. Remote Sens 14(6):1337. https://doi.org/10.3390/rs14061337
24. Maraveas C, Bartzanas T (2021) Application of Internet of Things (IoT) for optimized greenhouse environments. AgriEngineering 3(4). https://doi.org/10.3390/agriengineering3040060

25. McCaig M, Rezania D, Dara R (2023) Framing the response to IoT in agriculture: A discourse analysis. Agric Syst 204:103557. https://doi.org/10.1016/j.agsy.2022.103557
26. Narvekar C, Haider F (2022) AI-based crop monitoring using IoT. Int J Res Appl Sci Eng Technol (IJRASET) 10(5). https://doi.org/10.22214/ijraset.2022.42396
27. Bersani C, Ruggiero C (2022) Internet of Things approaches for monitoring and control of smart. greenhouses Ind 4 0 Energies 15(10):3834. https://doi.org/10.3390/en15103834
28. Mamatha V, Kavitha JC (2023) Machine learning-based crop growth management in greenhouse environment using hydroponics farming techniques. Measurement: Sens 25:100665. https://doi.org/10.1016/j.measen.2023.100665
29. Sarr AB, Sultan B (2023) Predicting crop yields in Senegal using machine learning methods. Int J Climatol 43(4). https://doi.org/10.1002/joc.7947
30. Rashid M, Bari BS (2021) A comprehensive review of crop yield prediction using machine learning approaches with special emphasis on palm oil yield prediction. IEEE Access. https://doi.org/10.1109/ACCESS.2021.3075159
31. Benyezza H, Bouhedda M, Kara R, Rebouh S (2023) Smart platform based on IoT and WSN for monitoring and control of a greenhouse in the context of precision agriculture. Internet Things 23:100898. https://doi.org/10.1016/j.iot.2023.100898
32. ThingSpeak (2025) Retrieved March 15, 2025, from https://thingspeak.com/

Figures

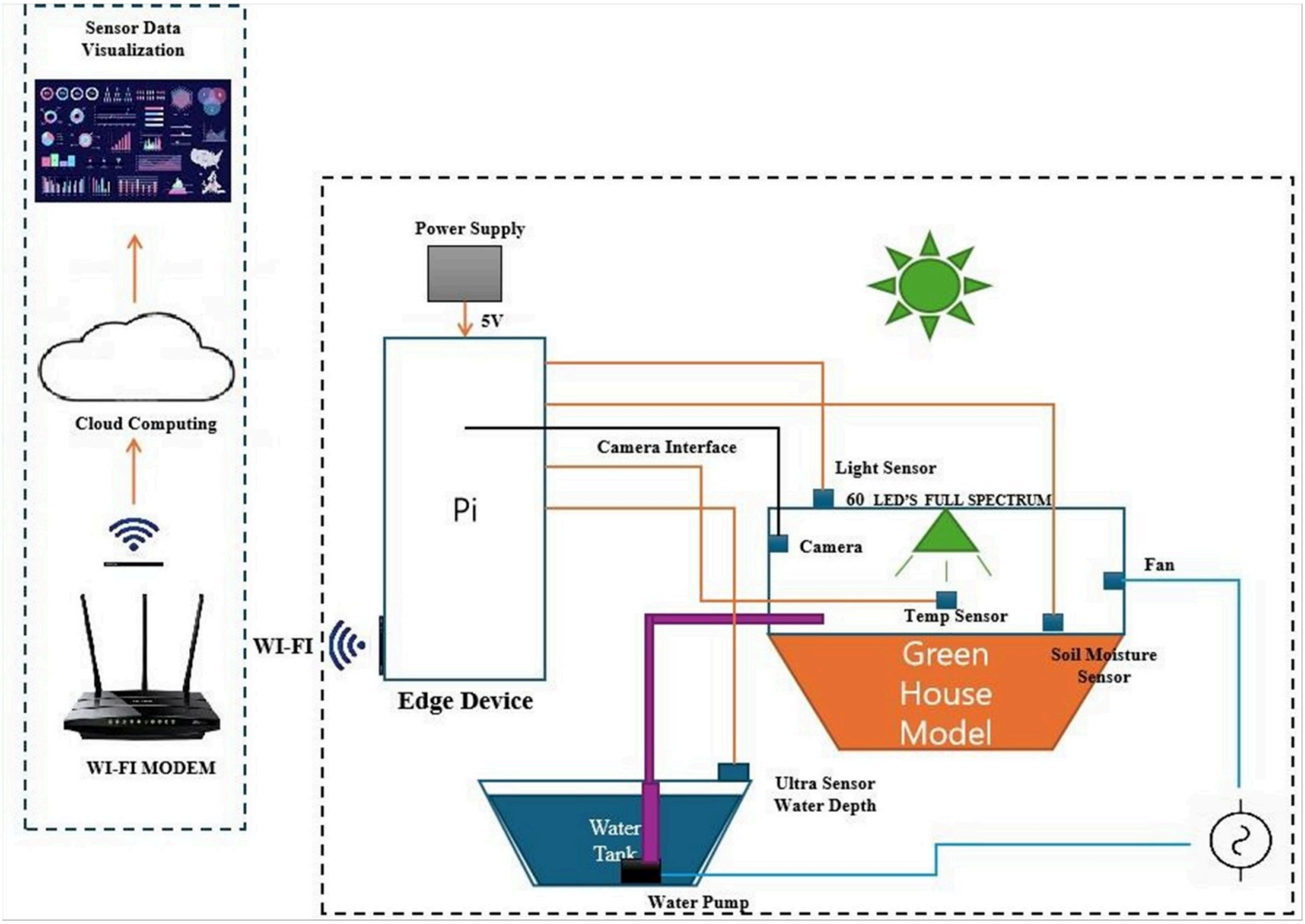


Figure 1

Greenhouse system architecture

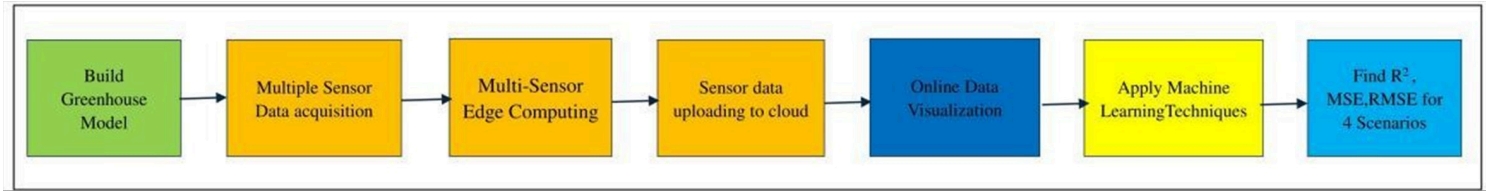


Figure 2

Crop Monitoring System

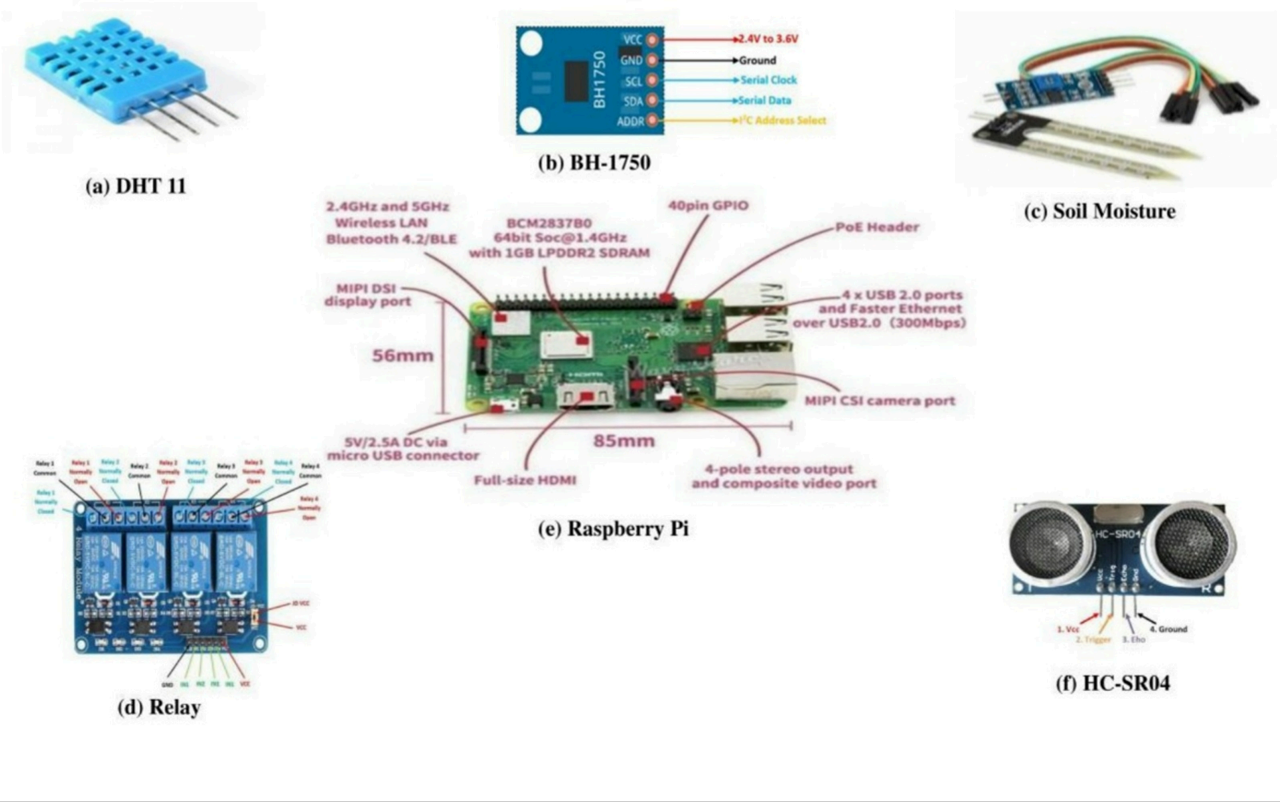


Figure 3

(a) DHT11- sensor (b) BH1750- light sensor pinout (c) Soil moisture sensor module (d) Four-channel relay module (e) Raspberry Pi 3B+ (f) Ultrasonic sensor

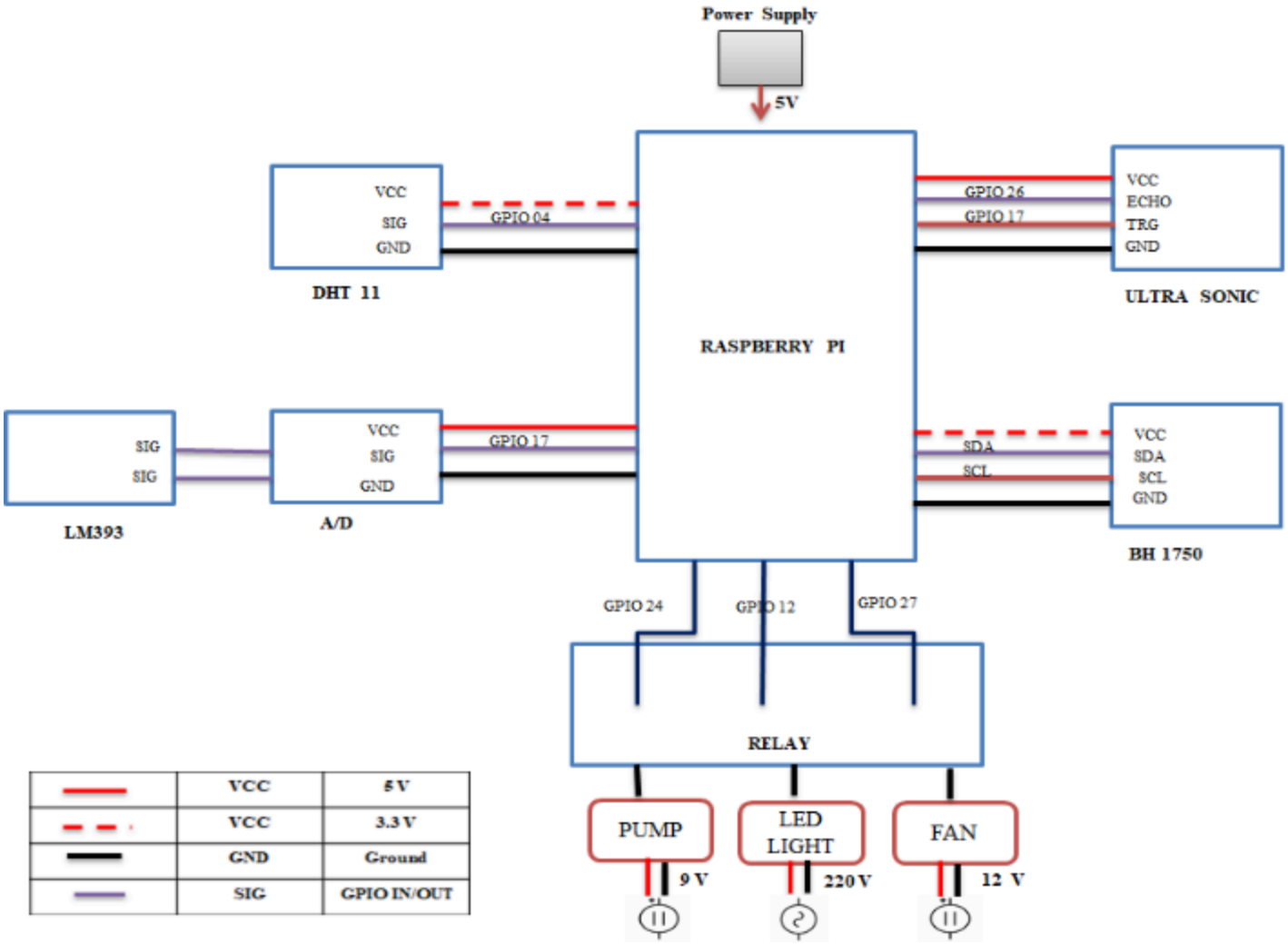


Figure 4

Pin Configuration of the Greenhouse Monitoring System

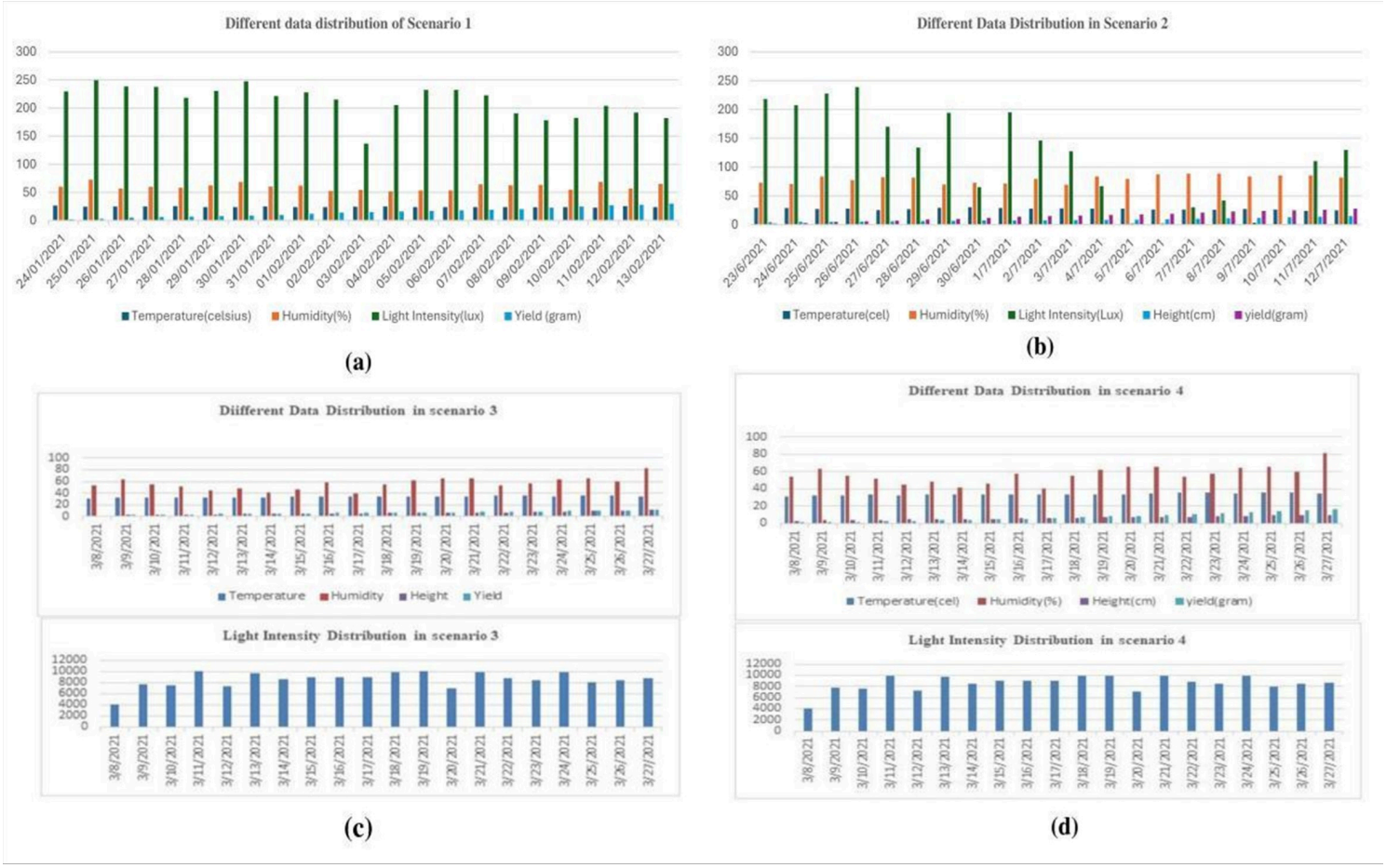


Figure 5

(a) Distribution of different data in scenario 1 (b) Scenario 2 (c) Scenario 3 (d) Scenario 4

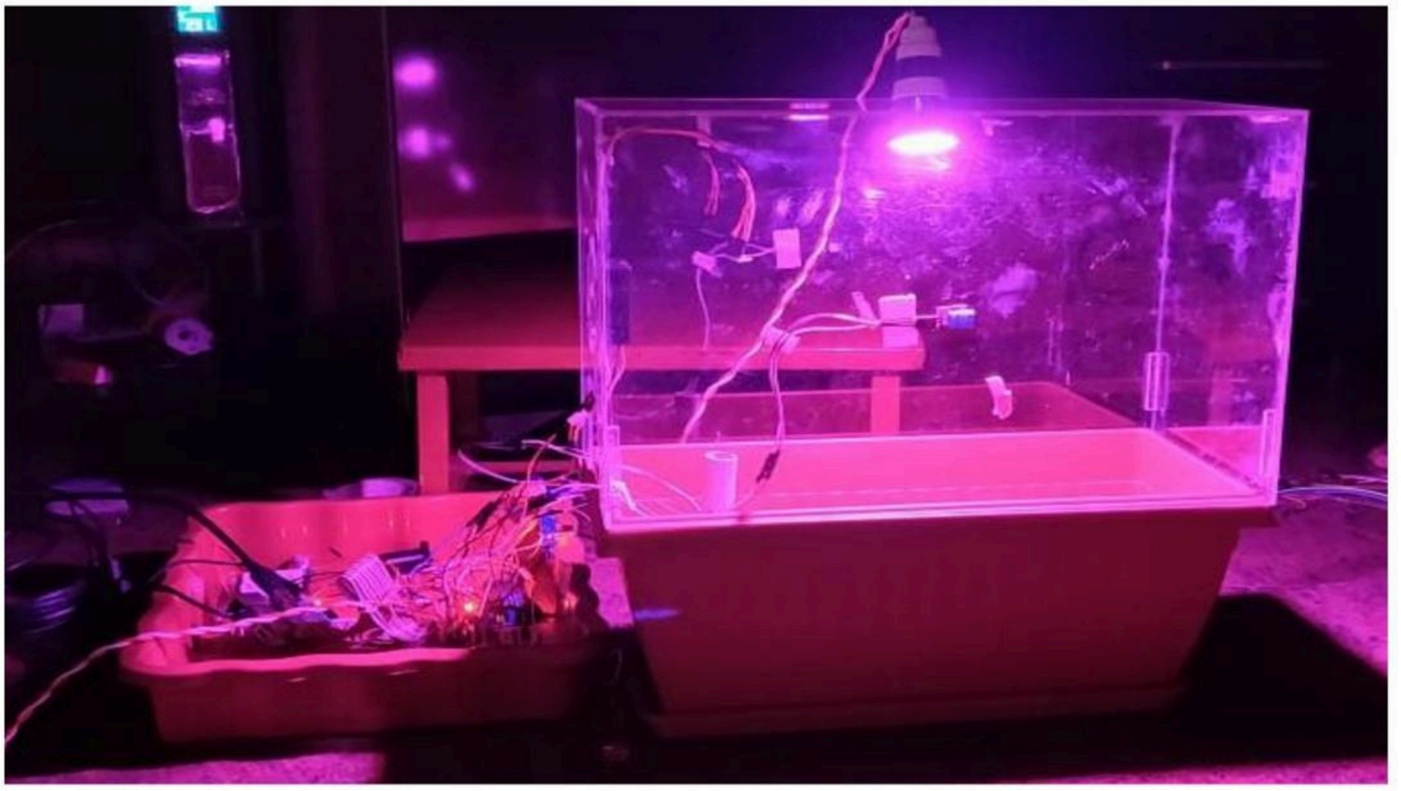


Figure 6

Experimental greenhouse setup

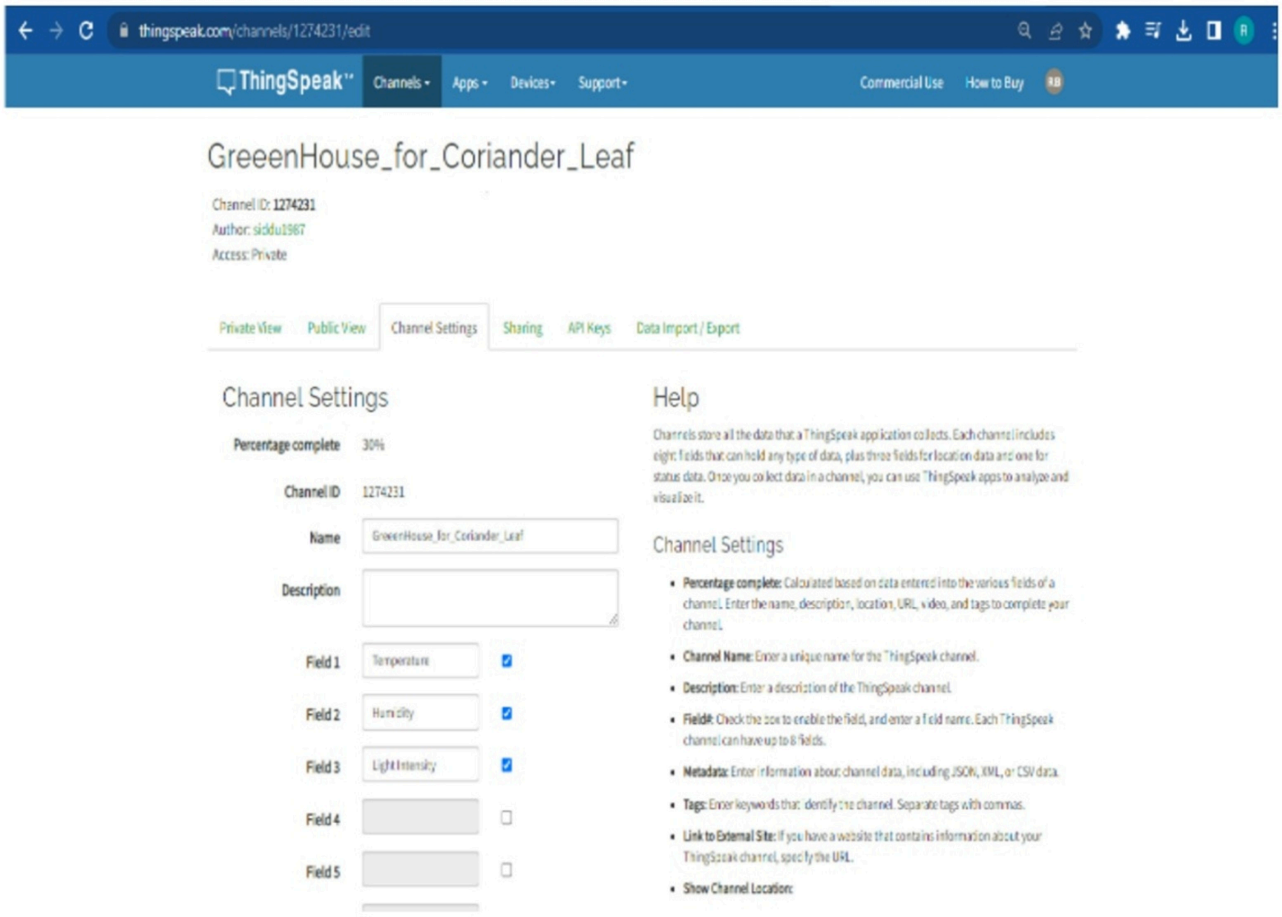


Figure 7

GUI of ThingSpeak cloud

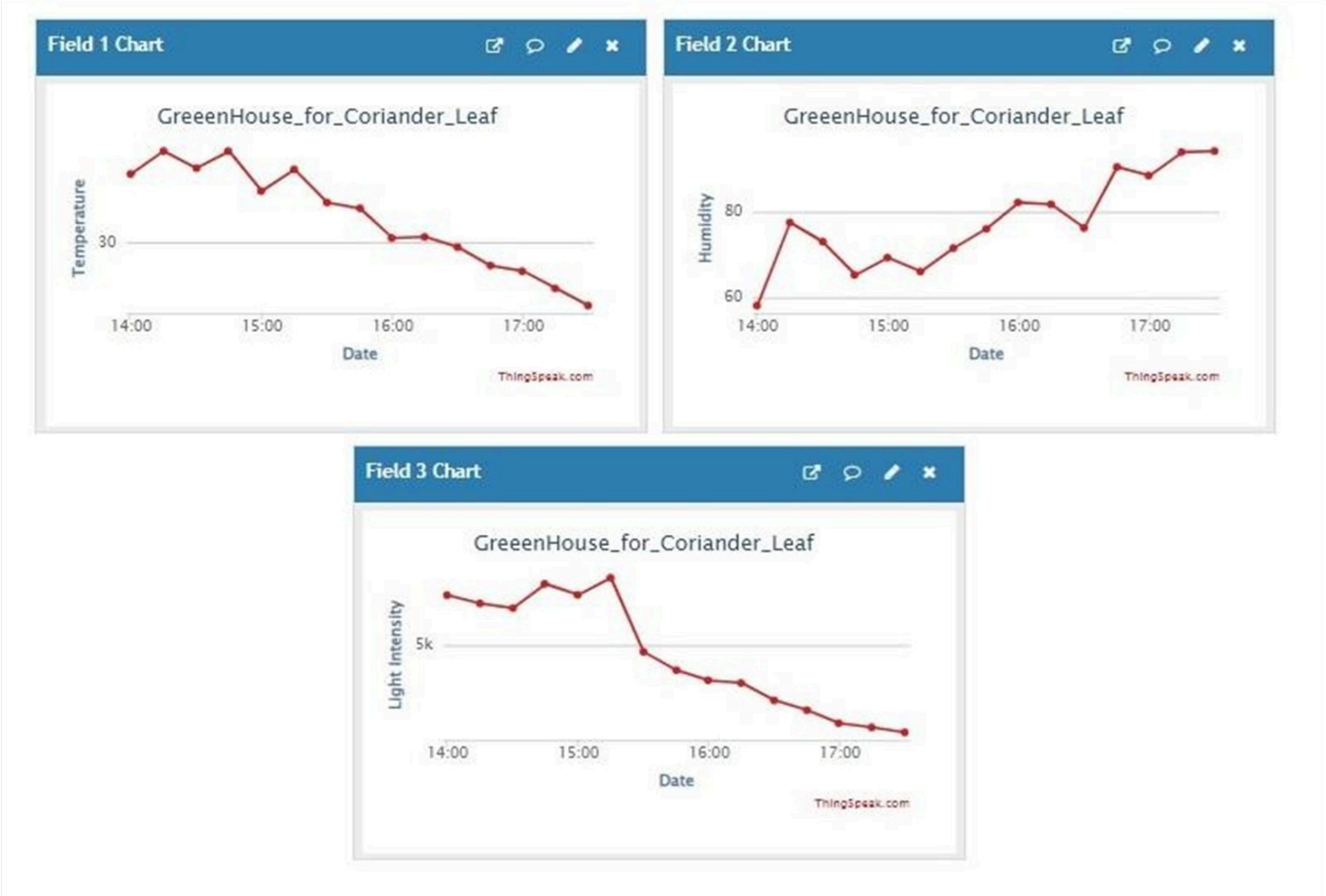


Figure 8

Real-Time Environmental Parameter Tracking Using ThingSpeak