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Sustainable greenhouse using IoT and machine learning to optimize the microclimate for lettuce cultivation

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ABSTRACT

Sustainable agriculture faces increasing challenges due to climate variability, which affects crop productivity and resource efficiency. This study proposes a sustainable greenhouse system that integrates internet of things (IoT) sensors and machine learning models to optimize the microclimate for lettuce cultivation. Environmental data, including temperature, humidity, and light intensity, were collected through IoT sensors and processed using machine learning algorithms, specifically neural networks and support vector machines (SVM), implemented on the Orange data mining platform. The results indicate that the neural network model achieved superior performance, reaching an accuracy of 99.99% in predicting optimal greenhouse climate conditions, outperforming the SVM model. The best-performing model was subsequently implemented on an Arduino-based IoT system to automatically regulate greenhouse conditions. The proposed system improved resource efficiency and supported optimal lettuce growth while promoting sustainable agricultural practices. These findings demonstrate that integrating IoT and machine learning can enhance greenhouse management, contributing to climate-resilient agriculture and improved food production systems.

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1. INTRODUCTION

Agriculture plays a crucial role in the Peruvian economy and in ensuring food security. In recent years, the population has shown growing concern about food quality and safety, particularly regarding contaminants and residues associated with agricultural production. This trend has increased the demand for sustainable agricultural strategies capable of reducing environmental risks while promoting ecosystem regeneration and healthier food systems [1], [2]. However, agricultural production remains vulnerable to several factors throughout the food supply chain, including harvesting, transportation, processing, and storage, where contamination and product deterioration may occur.

Climate change has intensified these challenges, especially in countries with high agricultural dependence such as Peru. Variations in temperature and humidity can accelerate the spread of pests and plant diseases, negatively affecting crop productivity and food safety. In this context, the integration of the internet of things (IoT) into agriculture has emerged as a promising technological approach for monitoring environmental conditions, improving crop management, and optimizing agricultural production. IoT systems allow continuous monitoring of variables such as temperature, humidity, and solar radiation, providing real-time information that supports more precise agricultural decisions. Nevertheless, the adoption of these technologies still faces several limitations, including implementation costs, cybersecurity concerns, and limited technical training among rural farmers [3]–[5].

Greenhouse cultivation represents an effective strategy for mitigating environmental variability by providing controlled conditions for plant development. Through the regulation of climatic factors such as temperature, humidity, and light exposure, greenhouse systems can improve crop productivity and quality while reducing exposure to pests and extreme weather conditions [6]–[8]. In particular, lettuce is one of the most widely cultivated horticultural crops in Peru and is highly sensitive to environmental fluctuations that may disrupt its growth cycle and reduce yields. For this reason, the use of controlled agricultural environments combined with sustainable practices such as regenerative agriculture has gained increasing attention in recent years [9]–[11].

Recent advances in IoT and artificial intelligence (AI) have further expanded the potential of smart agriculture. By integrating sensors, data processing systems, and machine learning algorithms, agricultural systems can analyze environmental data and automatically adjust cultivation conditions to improve crop performance. These technologies enable real-time monitoring, improved resource management, automation of agricultural processes, and reduction of operational costs, ultimately contributing to more efficient and sustainable farming systems [12]–[15]. Despite these advances, most existing studies primarily focus on environmental monitoring rather than on integrating predictive machine learning models capable of optimizing greenhouse microclimate conditions in real time [16]–[19].

Despite the significant progress in IoT and AI applications in agriculture, current approaches still lack robust integration between real-time sensing systems and predictive machine learning models for precise microclimate optimization. Furthermore, there is limited research focusing on the application of such integrated systems for specific crops like lettuce in developing agricultural contexts such as Peru, where technological adoption and environmental challenges differ from those in more industrialized regions [20]-[22].

Therefore, this study aims to design, develop, and evaluate a sustainable greenhouse prototype that integrates IoT sensors with machine learning models to optimize the microclimate for lettuce cultivation. The proposed system collects environmental data and applies artificial neural networks (ANN) and support vector machine (SVM) algorithms to predict optimal climatic conditions for crop growth. The main contributions of this research include: i) the design of an IoT-based data acquisition system for real-time environmental monitoring, ii) the comparative evaluation of machine learning models for climate prediction, and iii) the implementation of an intelligent control mechanism to improve environmental regulation. This approach enhances greenhouse efficiency and supports sustainable agricultural practices through data-driven decision-making.

2. METHOD

This section describes the design of the electronic circuit, the construction of the automated greenhouse prototype, and the implementation of machine learning models used to analyze and optimize the greenhouse microclimate. These stages enable the monitoring and regulation of environmental variables influencing lettuce growth through the integration of IoT technologies and data-driven approaches.

2.1. Electronic circuit design

The electronic circuit was designed to integrate environmental sensors, actuators, and microcontrollers to enable automated monitoring and control of the greenhouse microclimate. The system architecture is based on an Arduino Uno microcontroller, which functions as the main controller responsible for acquiring sensor data and activating actuators based on predefined environmental thresholds.

The wiring diagram assigns specific nomenclature to each pin connection to facilitate system integration and scalability. Identical pin labels between components indicate direct electrical connections. For instance, the UV sensor includes three pins labeled OUT2, 5 VDC, and GND, which are connected to the corresponding Arduino Uno pins. This structured configuration ensures reliable communication between sensors, actuators, and control modules. The complete circuit configuration is shown in Figure 1, which illustrates the integration of sensors, actuators, LCD display, relay modules, and microcontroller units. This configuration enables real-time acquisition and automated regulation of key environmental parameters inside the greenhouse.

2.2. Construction of the greenhouse prototype

A small-scale greenhouse prototype was developed to provide a controlled environment for lettuce cultivation and to validate the proposed IoT-based monitoring and control system. The structure was designed using lightweight and low-cost materials to ensure ease of replication and scalability.

The main structure was built using ½-inch PVC pipes and a 5 mm acrylic base, providing mechanical stability while maintaining adequate light transmission. Table 1 summarizes the materials used in the construction process, including their quantities and dimensions.

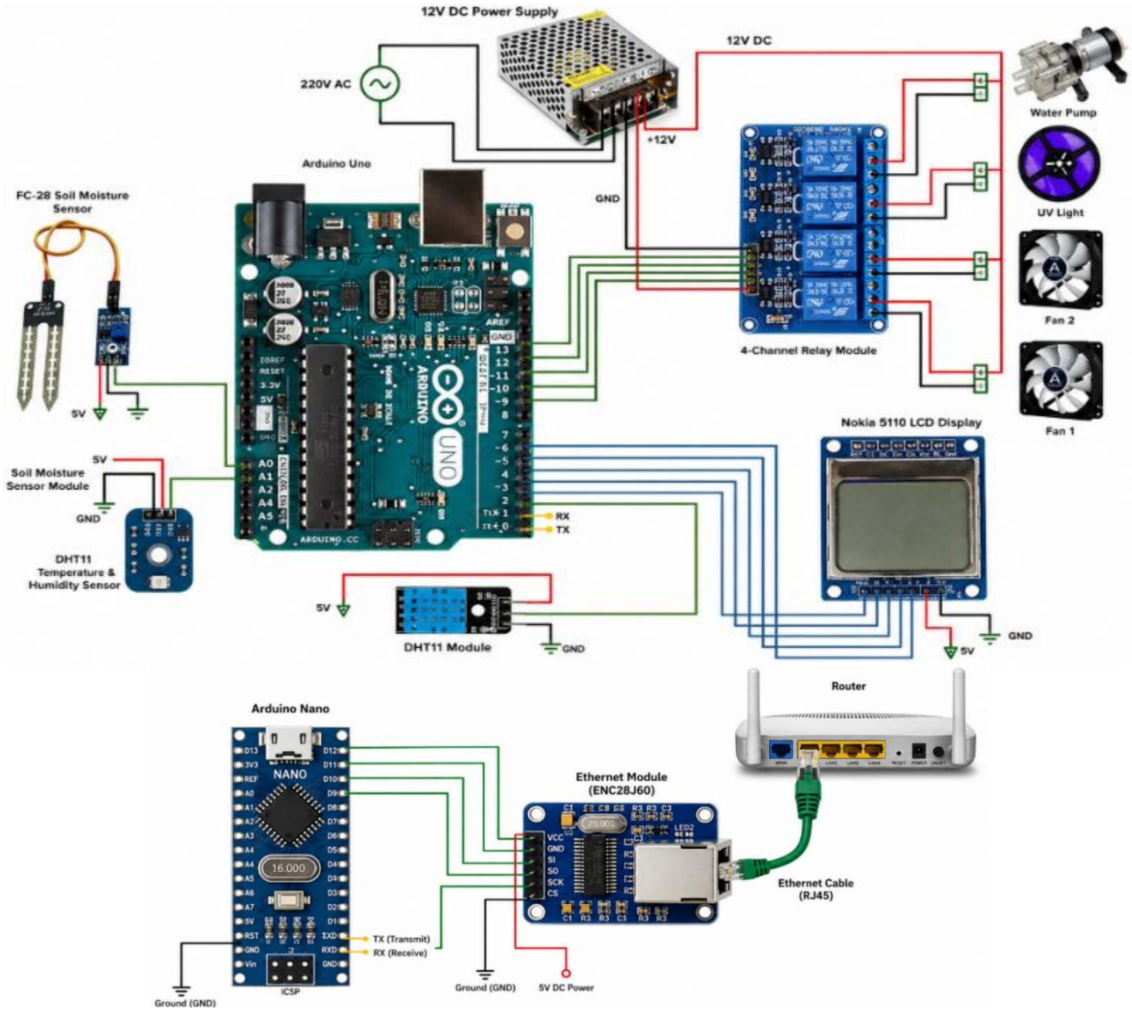


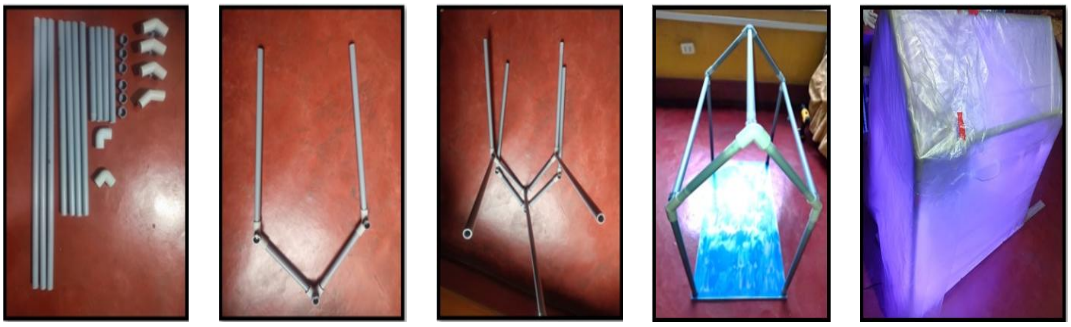
Figure 1. Wiring diagram of sensors, actuators, LCD display, 4-channel relay, and Arduino modules

Table 1. Greenhouse materials

Item	Material	Quantity	Measurements (cm)		
1	½" PVC water pipe	4	24	50	70
2	½" 45° elbow	4			
3	½" 90° elbow	2			
4	½" female plug	10			
5	Acrylic sheet	2		80×45	
6	Saw blade	1			
7	PVC glue	1			
8	3×16 mm screws	12			
9	Plastic bag	6		80×40	
10	UTP cable (m)	7			
11	Black corrugated hose (m)	8			
12	Organic prepared soil (kg)	20			

The construction process of the greenhouse structure is illustrated in Figure 2. Initially, the PVC pipes were measured and cut to the required dimensions (Figure 2(a)). Subsequently, 45° and 90° elbows were assembled using adhesive and reinforced with screws to ensure structural stability (Figure 2(b)). Then, 24 cm and 50 cm pipes were connected to form the main frame, followed by the integration of 70 cm vertical supports to complete the structure (Figure 2(c)). The acrylic base was then attached (Figure 2(d)), and finally, the structure was covered with plastic material, leaving designated openings for ventilation and access (Figure 2(e)).

Within the IoT framework, Table 2 presents the sensors and actuators used in the system. Three primary sensors were selected based on their measurement range and compatibility with the crop requirements: the DHT11 sensor for temperature and relative humidity, the UV sensor for radiation monitoring, and the FC-28 soil moisture sensor for irrigation control. These sensors enable the acquisition of critical environmental parameters for lettuce cultivation. The system also incorporates actuators responsible for environmental regulation, including a DC motor pump for irrigation, two 12 V fans for temperature and humidity control, and a UV LED strip for supplemental lighting. This integration allows automated responses to environmental variations, improving crop conditions and system efficiency.



(a) (b) (c) (d) (e)

Figure 2. Greenhouse design; (a) cutting of pipes, (b) joining of elbows and plugs, (c) joining of structures, (d) joining of structure and base, and (e) lining of structure

Table 2. Sensors and actuators for the greenhouse

Item	Sensors and actuators	Quantity	Item	Sensors and actuators	Quantity
1	UV light roll	1	7	YL-69	1
2	12 V DC motor pump	1	8	UV-SENS	1
3	Fan 12 V DC	2	9	SD module	1
4	Arduino One	1	10	ENC28J60	1
5	Arduino Nano	1	11	HW-316	1
6	DHT11	1			

Figure 3 presents the system flowchart based on a master–slave architecture. The Arduino Uno acts as the master controller, responsible for reading environmental variables such as temperature, soil moisture, and UV radiation, and making control decisions based on predefined thresholds. For example, when the temperature falls below 15 °C, the UV LED system is activated to maintain optimal conditions, whereas temperatures above 20 °C trigger the activation of cooling fans.

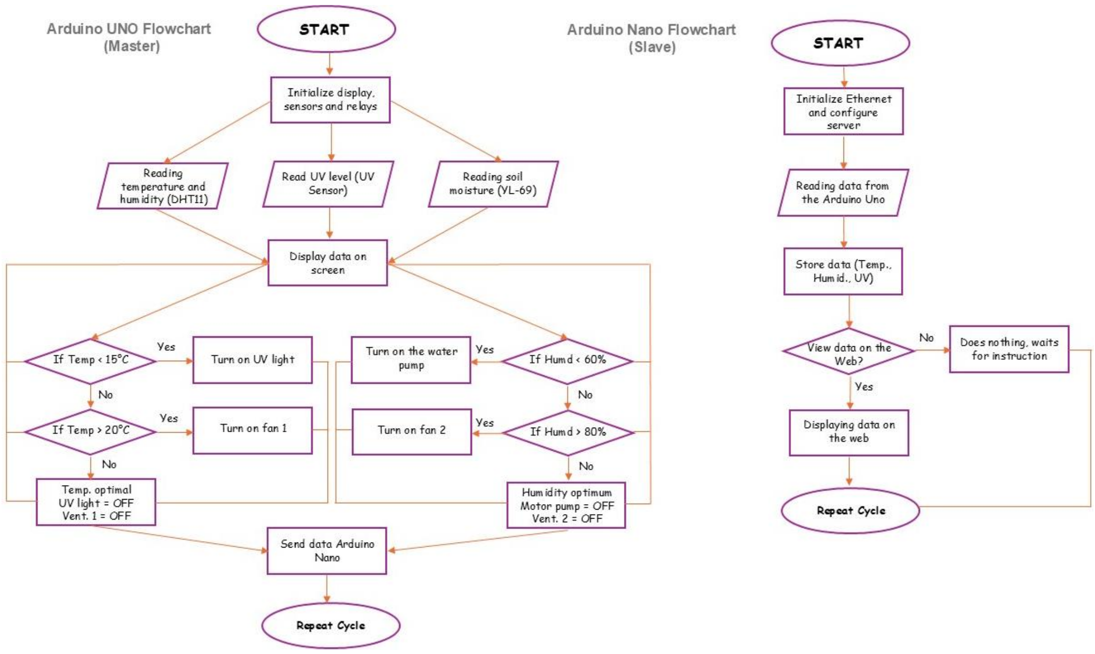
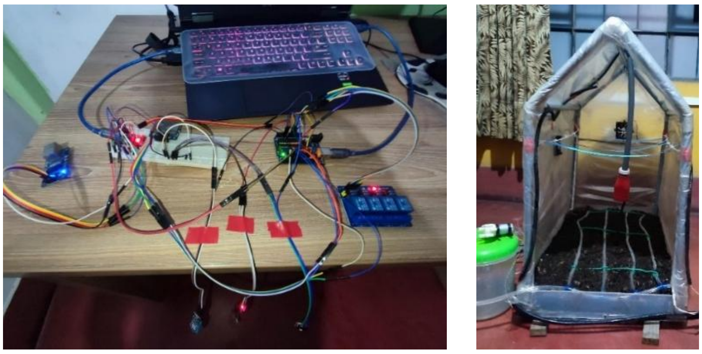


Figure 3. Arduino Uno and Arduino Nano flowchart operation

Similarly, soil moisture levels are continuously monitored to regulate irrigation through the motor pump. When moisture levels fall below 60%, the irrigation system is activated, while excessive humidity levels above 80% trigger ventilation mechanisms.

The Arduino Nano operates as a slave unit, handling data transmission, storage, and visualization through a web interface. It receives data from the master controller and dynamically displays system status, enabling remote monitoring without interfering with control decisions. This architecture ensures efficient system operation by separating control and visualization tasks, improving reliability and scalability.

The testing and installation of sensors and actuators are illustrated in Figure 4. Initially, preliminary evaluations were conducted to ensure accurate readings of temperature, UV radiation, and soil moisture, as well as to verify the proper functioning of the relays under predefined conditions (Figure 4(a)). Subsequently, the system wiring was carried out using UTP cable, selected for its compatibility with the sensor terminals and the Arduino platform (Figure 4(b)). Sensors were strategically placed at the center of the greenhouse to maximize measurement accuracy. In addition, the UV LED strip was installed at the top to ensure uniform light distribution, two fans were mounted to regulate temperature and humidity, and the motor pump was positioned near a water container to facilitate irrigation.



(a) (b)

Figure 4. Testing of sensors and actuators; (a) installation of sensors and (b) actuators in the greenhouse

2.3. Machine learning application

Environmental data collected by IoT sensors were stored and exported in CSV format for machine learning analysis. The dataset was processed using the Orange data mining platform to evaluate predictive models capable of identifying optimal greenhouse microclimate conditions. The models analyze environmental variables such as temperature, soil moisture, and UV radiation to predict whether the greenhouse conditions are optimal for lettuce growth. This approach enables data-driven decision-making and enhances system automation.

2.3.1. Data processing

The dataset consists of 2,999 records containing temperature, soil humidity, and UV radiation data. A training set comprising 70% of the data was used to build the models, while the remaining 30% was reserved for testing. Data normalization was applied to ensure consistency across variables and improve model performance. Additionally, derived features were created, including temperature condition, soil moisture condition, and UV condition, which classify environmental values into categories such as optimal, excessive, or deficient. These preprocessing steps reduce noise, enhance pattern recognition, and improve the predictive accuracy of the machine learning models. A sample of the dataset is presented in Table 3.

2.3.2. Application of machine learning models

The greenhouse microclimate is inherently dynamic and nonlinear, requiring robust models capable of capturing complex relationships among environmental variables [21]-[24]. In this study, two machine learning techniques were applied: ANN and SVM.

- Neural networks: suitable for capturing nonlinear relationships, mimicking brain-like learning and adaptability [25]. In this study, the ANN model predicts whether greenhouse conditions are optimal based on temperature, soil moisture, and UV radiation data.
- SVM: useful for classification tasks, separating climate data (temperature, humidity, and UV) into categories such as sunny, rainy, or cold [26]. In this context, SVM is used to classify environmental conditions into categories such as optimal, excessive, or deficient.

Table 3. Database

Item	Temperature	Soil humidity (%)	UV level	T. condition	S. condition	UV condition
1	21.8	72	1	Excessive	Optimal	Optimal
2	20.6	82	3	Optimal	Excessive	
3	20.6	79	3		Optimal	
4	20.6	79	3			
5	20.6	79	3			
6	20.6	78	3			
7	20.6	78	3			
8	20.6	78	3			
9	20.6	78	3			
10	20.6	77	3			
11	20.6	77	3			
12	20.6	77	3			
13	20.6	77	3			
14	20.6	77	3			
15	20.6	76	3			
16	21.8	1	4	Excessive	Deficient	Excessive
17	21.8	72	4		Optimal	
18	21.8	72	4			
19	21.8	72	4			

Figure 5 shows two common machine learning approaches. On the left is a neural network, represented as interconnected nodes that simulate the way the human brain processes information and learns complex patterns. On the right is an SVM, illustrated by data points separated by a line that defines the optimal classification boundary between different classes.

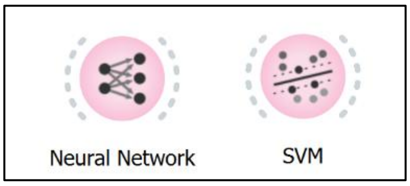


Figure 5. Intelligent models

In the training process (see Figure 6), the two machine learning models (neural networks and SVM) are selected and connected to the "Test and Score" widget. This indicates that each model is trained with the same data, and its performance is evaluated using the same parameters. The results of the trained models can be analyzed in the viewer called a distribution diagram (see Figure 7).

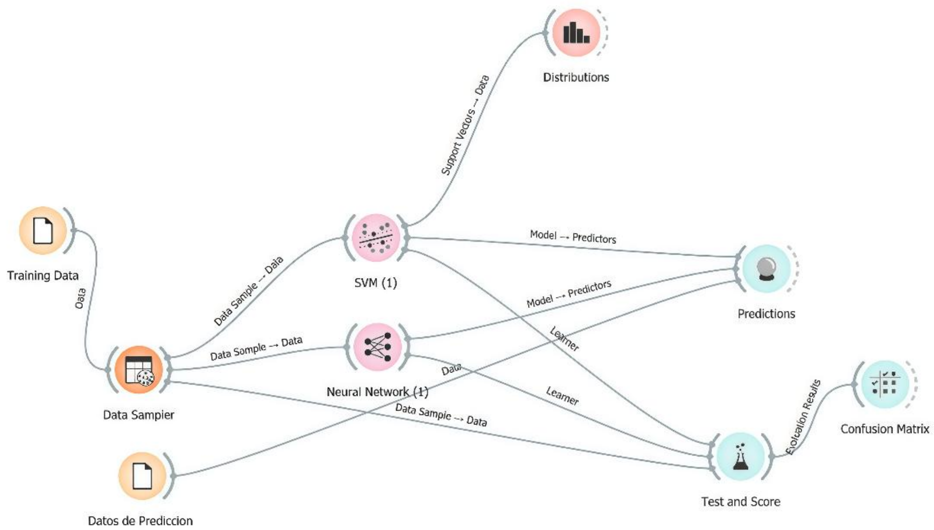


Figure 6. Training in intelligent models

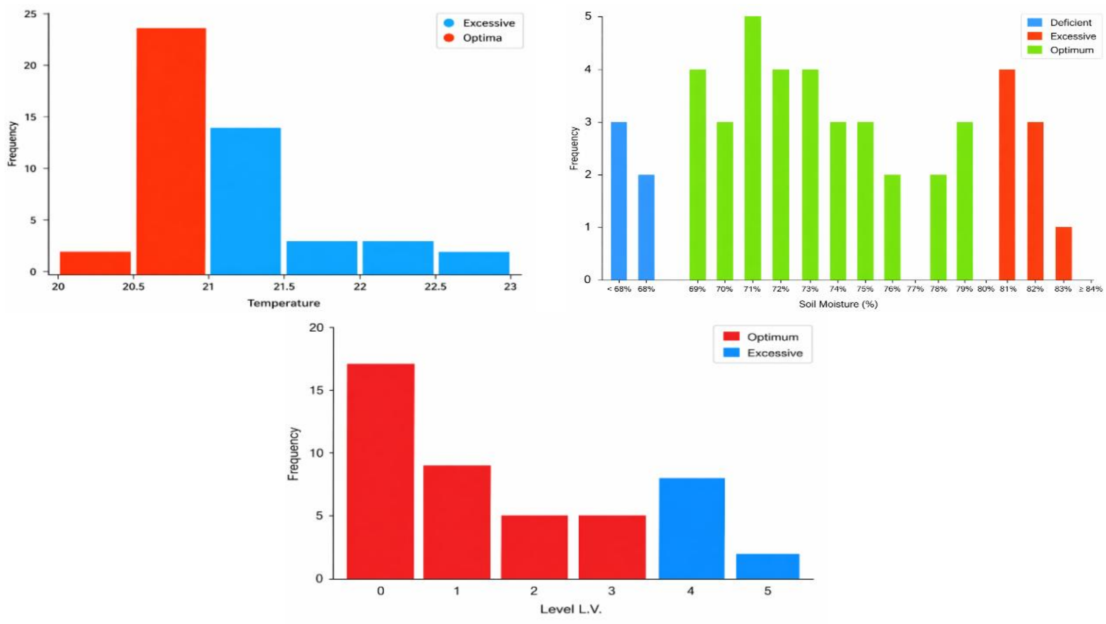


Figure 7. Distribution diagram

3. RESULTS AND DISCUSSION

The performance of the machine learning models was evaluated using several classification metrics obtained through the Test and Score procedure. This evaluation compares the predicted results generated by each model with the actual outcomes from the test dataset, allowing the reliability and predictive capability of each algorithm to be assessed.

Table 4 presents the performance comparison between the SVM and the ANN models using evaluation metrics including area under the curve (AUC), F1-score, precision, recall, and Matthews correlation coefficient (MCC). The results indicate that both models achieved high predictive performance; however, the ANN consistently outperformed the SVM across all evaluation metrics. In particular, the ANN obtained an AUC value of 0.999 compared to 0.988 for the SVM, demonstrating superior classification capability and a stronger ability to discriminate between optimal and non-optimal greenhouse conditions. Similarly, slight improvements in F1-score, precision, recall, and MCC indicate that the ANN provides more accurate and stable predictions.

Table 4. Performance comparison: SVM vs. neural network

Model	AUC	F1-score	Precision	Recall	MCC
SVM	0.988	0.990	0.990	0.990	0.980
Neural network	0.999	0.991	0.991	0.991	0.981

The superior performance of the ANN can be attributed to its ability to model complex nonlinear relationships among environmental variables such as temperature, soil humidity, and UV radiation. Greenhouse microclimates are inherently dynamic systems influenced by multiple interacting factors, making them difficult to model using linear or semi-linear approaches. ANN models are particularly effective in capturing these nonlinear interactions due to their layered architecture and adaptive learning capabilities. In contrast, the performance of SVM is highly dependent on the selection of kernel functions and hyperparameters. Improper tuning may limit its ability to generalize complex environmental patterns, especially in datasets with high variability. Furthermore, ANN models demonstrate greater flexibility when handling continuous sensor data and can adapt more effectively to variations in environmental conditions. This explains the consistently higher predictive accuracy observed in the ANN model compared to the SVM.

ROC analysis: as a second metric, the ROC curve analysis was performed for the neural network and SVM in predicting the optimal climate for the greenhouse [27]. ROC curve analysis was performed to further evaluate the classification performance of both models. As shown in Figure 8, the ANN achieved an AUC value of 0.999, indicating near-perfect classification performance in distinguishing optimal greenhouse conditions. The SVM model obtained an AUC value of 0.988, which also reflects strong performance but with slightly lower discrimination capability. The ROC curve illustrates the trade-off between true positive rate and false positive rate. The ANN curve is closer to the top-left corner of the graph, indicating better sensitivity and specificity. This confirms that the ANN model is more reliable in identifying optimal microclimate conditions.

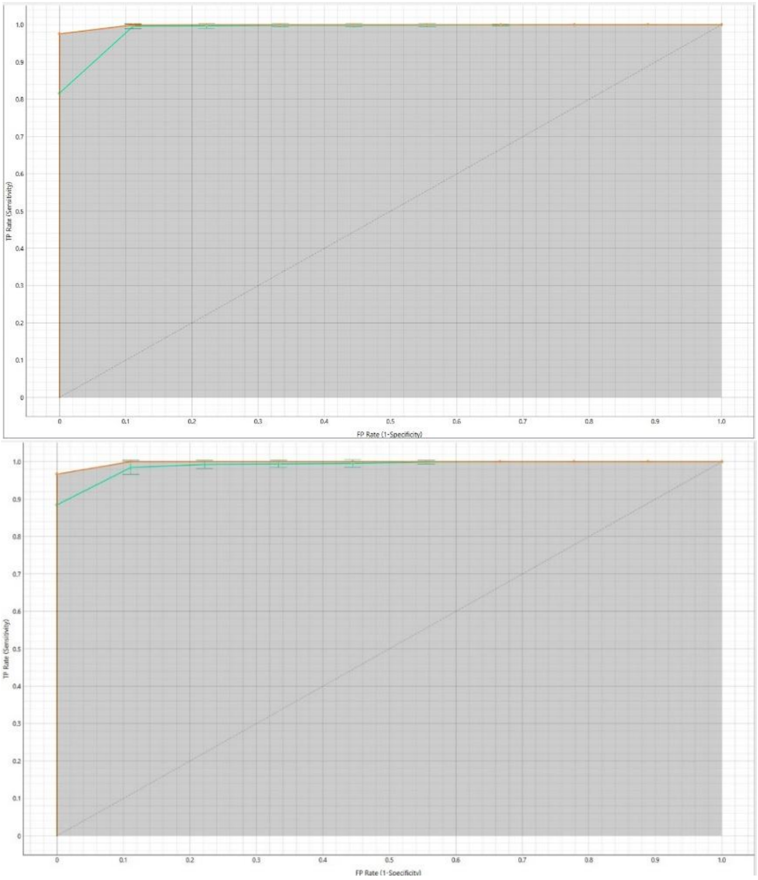


Figure 8. Distribution diagram

Performance curve: Figure 9 presents the performance curve analysis for both models. The ANN achieved a value close to 1, indicating highly reliable predictive performance and strong model stability. In contrast, the SVM model obtained a slightly lower value (0.991), demonstrating good performance but reduced predictive consistency. This result suggests that the ANN model is more robust in handling variations in environmental data and is better suited for real-time greenhouse applications where conditions may change dynamically.

Confusion matrix: the fourth metric analyzed was the confusion matrix [28]. As shown in Figure 10, the SVM model correctly classified 1,254 samples as “NOT OPTIMAL,” with 13 false negatives. For the “OPTIMAL” category, the model achieved 826 true positives and 7 false positives. Similarly, the ANN model correctly classified 1,255 samples as “NOT OPTIMAL,” with 13 false negatives, and achieved 826 true positives with only 6 false positives. This indicates a slight reduction in classification errors compared to the SVM model. The lower number of false positives in the ANN model is particularly important, as it reduces incorrect activation of greenhouse control systems, leading to more efficient resource utilization and improved system reliability.

Overall, both models demonstrate strong predictive capability; however, the ANN consistently shows superior performance across all evaluation metrics. This advantage is primarily due to its ability to generalize complex nonlinear relationships among environmental variables and adapt to dynamic conditions. The results confirm that machine learning techniques can effectively predict greenhouse microclimate conditions, enabling more efficient and automated environmental control within IoT-based agricultural systems. By accurately identifying optimal climate conditions for lettuce cultivation, the proposed system enhances decision-making processes, improves resource efficiency, and supports sustainable agricultural practices. Furthermore, the integration of IoT and machine learning provides a scalable and intelligent solution for modern greenhouse management, contributing to climate-resilient agricultural systems.

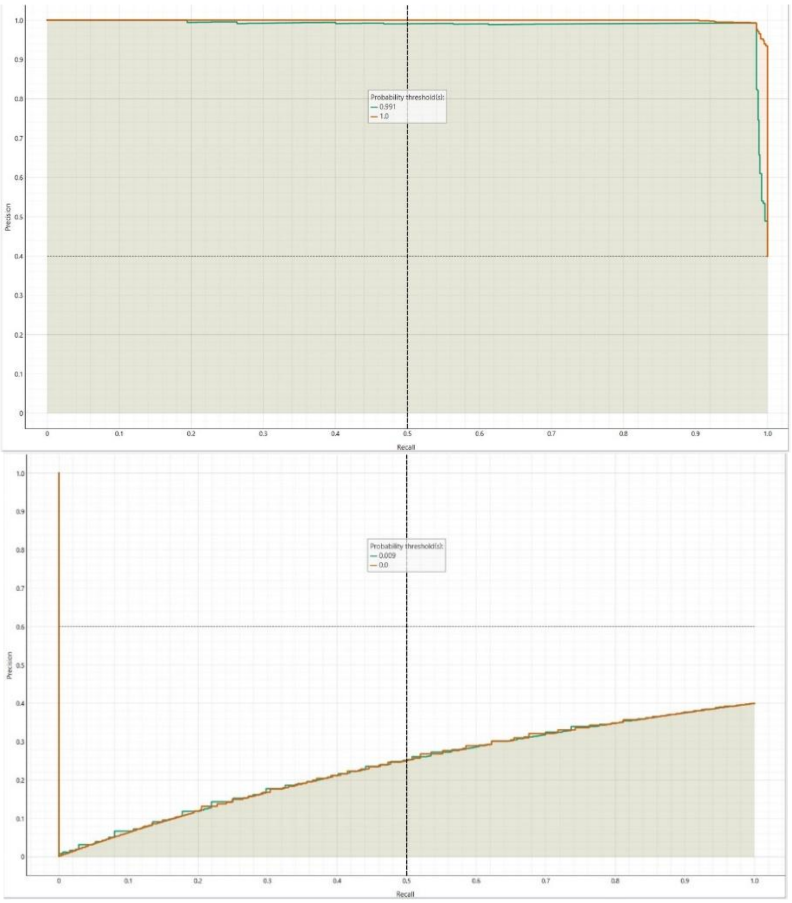


Figure 9. Yield curve

Actual \ Predicted	NO OPTIMAL	OPTIMAL	Σ
NO OPTIMAL	1254	7	1261
OPTIMAL	13	826	839
Σ	1267	833	2100

Actual \ Predicted	NO OPTIMAL	OPTIMAL	Σ
NO OPTIMAL	1255	6	1261
OPTIMAL	13	826	839
Σ	1268	832	2100

Figure 10. Confusion matrix

4. CONCLUSION

This study presented the design, development, and implementation of an intelligent greenhouse system that integrates IoT technologies with machine learning models to optimize the microclimate for lettuce cultivation. The proposed system enables continuous monitoring of key environmental variables, including temperature, soil moisture, and ultraviolet radiation, facilitating automated and data-driven decision-making for greenhouse management.

The experimental results demonstrated that both models achieved high predictive performance; however, the ANN consistently outperformed the SVM across all evaluation metrics. In particular, the ANN achieved an accuracy of 99.9% and an AUC value of 0.999, compared to 99.0% accuracy and 0.988 AUC for the SVM. Furthermore, the confusion matrix analysis confirmed that the ANN reduced classification errors, particularly false positives, improving the reliability of the system in identifying optimal greenhouse conditions. These findings indicate that ANN models are more suitable for modeling complex and nonlinear greenhouse microclimate dynamics, enabling more precise environmental control. The integration of IoT-based monitoring with machine learning prediction enhances greenhouse efficiency by optimizing resource utilization, reducing unnecessary actuator activation, and supporting sustainable agricultural practices.

The main contribution of this research lies in the development of an integrated IoT–machine learning framework capable of predicting and regulating greenhouse conditions in real time, providing a scalable solution for intelligent agriculture. For future work, it is recommended to validate the proposed system in larger-scale greenhouse environments, extend its application to different crop types, and integrate cloud-based platforms for remote monitoring and data analysis. Additionally, incorporating a wider range of environmental sensors and exploring advanced machine learning techniques could further improve system accuracy, adaptability, and scalability.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
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Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

INFORMED CONSENT

Not applicable.

ETHICAL APPROVAL

Not applicable.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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