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ARTIFICIAL INTELLIGENCE EVENT-TRIGGERED CONTROL SYSTEM FOR REAL-TIME MONITORING AND PREDICTION OF GREENHOUSE CONDITIONS

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ABSTRACT

Greenhouse farming is often limited by unstable environmental conditions and inefficient manual control methods. The paper designs an Artificial Intelligence Event-Triggered Control System (AIETCS) of real-time monitoring and prediction of greenhouse conditions using an Artificial Neural Network (ANN). A simulation based, quantitative methodology was embraced. Important environmental parameters were defined in terms of temperature, relative humidity, soil moisture, photo synthetically active radiation (PAR) and soil nutrients, between rainy and Harmattan seasons (2021-2024). Hardware interactions were modelled using Proteus simulation and data were pre-processed then used to train the ANN. The ANN was used to predict short-term greenhouse conditions and the event-triggered logic only used actuators when they were above their thresholds. Results show the ANN achieved high predictive accuracy (validation loss = 2.0761e-04, MAE = 0.028, R2=0.97R^2 = 0.97R2=0.97). Compared to baseline conditions, where deviations from ideal values reached 58% (soil moisture) and 39% (humidity), the AIETCS consistently reduced deviations to below 3.5% across all variables. The findings demonstrate that ANN-driven event-triggered control improves greenhouse stability, reduces resource wastage, and provides a scalable framework for precision agriculture in resource-constrained settings.

Keywords: Artificial Neural Network; Event-Triggered Control; Greenhouse Monitoring; Precision Agriculture

1. INTRODUCTION

Falana et al. (2024) define a greenhouse as a building surrounded with an objective of cultivating crops. It is meant to shield plants against poor climatic conditions and it generally comprises of frames composed of transparent substances like glass and polyethylene. The development of greenhouse farming, as well as other methods of controlled environment, has been designed to generate viable micro-climates to allow crops to grow all year round or during certain seasons (Maraveas et al., 2023). These technologies are also essential to produce vegetables, ornamentals, and high-value food crops in cold climates in the off-season when outdoor production is not feasible (Abou-Mehdi-Hassani et al., 2022).

In the world, countries are having difficulties to sustain the increasing food needs of its citizens. This crisis highlights the economic necessity to reconcile the population growth to the food security. The food production and quality enhancement requires modern technologies and precision agriculture techniques including greenhouse farming (Abdeen, 2024). To them, the implementation of electronic information systems in greenhouse farms can be used to create profound improvements in year-round production of food and positively affect the economies of nations (Kumar et al., 2022). Such systems are able to observe and regulate temperature, humidity, and light intensity to provide all the best conditions in growing crops (Singh et al., 2021).

Glasshouses or greenhouses are climate-controlled facilities that are available throughout the year to grow sensitive or out of season plants. They are classified according to shape, and such types as Gable, Flat arch, Raised dome, Sawtooth, Skillion, and Tunnel (Abdulquadri, 2023). The main role of these buildings is to protect crops against unfavorable factors like high or low temperatures, wind, hail, rain, snow, pests and diseases (Zhang et al., 2020). It is important to make sure that the greenhouses have optimal natural light intensity to produce crops more efficiently (Chen et al., 2023).

Conventionally used control of humidity, light, and temperature are not always effective. The manual observation of climate in human senses is not practical even to maintain climate 24/7, which creates demands on smart greenhouse technologies and electronic control systems (Bhatt, 2021). These challenges can be solved by creating cost-effective greenhouses that have features such as shading, air circulation by use of treated nets, and pests (Rahman et al., 2022). The process of climate control can be automated by smart systems that enhance efficiency and lead to less reliance on labor (Ghosh et al., 2023).

The previous greenhouse surveillance systems were based on wired sensor networks which added cablings and hampered farm operations. The wireless sensor networks (WSNs) have been used to handle such a problem, allowing mobility and decreasing clutter (Patel et al., 2021). WSNs together with machine learning make climatic monitoring in real-time without people (Lee et al., 2020). The technologies help to make communication between sensors and control units smooth to enhance the management of greenhouses (Al-Turjman et al., 2023).
In far off greenhouse areas, important climate activities can be forgotten as there will be no human supervision. Such activities as irrigation and light control should be automated and can be performed with the help of event-triggered approaches (ETA) (Rani et al., 2021). Actuators can be activated by controllers coded to act on WSN data depending on the particular climate needs related to the crop (Sharma et al., 2022). Implementation can become a complicated task; however with lower cost and dependable systems, this technology can be affordable to farmers (Mishra et al., 2023).
In Nigeria, farmer reluctance to invest in greenhouse agriculture stems from high setup costs, lack of expertise, and uncertainty about outcomes. A survey by Maisha Mazuri Consultancy (2023) revealed that over 83.25% of farmers practicing protected agriculture do not utilize greenhouse technology. This issue demands urgent attention, especially given Nigeria's economic challenges. Increased research and innovation, supported by universities and government initiatives, can promote awareness and adoption of modern agricultural practices (Okafor et al., 2024).

2. RESEARCH METHODOLOGY

Quantitative and simulation approach is the methodology that is adopted in this study. It was used to fulfill the study objective through the integration of system characterization, intelligent control system design, artificial intelligence integration, and validation through simulation. This approach starts with the description of greenhouse farming systems so as to learn the basic environmental variables that determine crop yield. Parameters of interest will be temperature, humidity, soil moisture and light intensity that will be investigated using both secondary data sources found in literature as well as primary data sources like existing greenhouse setups. It will be followed by the creation of an intelligent event-driven control system that will allow real-time monitoring and automatic reaction to any changes in the greenhouse environment. The predictive models will be constructed using a machine learning approach that will be able to learn on historical data and therefore spot anomalies or critical thresholds. The control logic will be programmed to take certain measures like irrigation, ventilation, or lighting modifications once the non-conformity to the ideal conditions is detected. The methodology also includes the design and development of a green house monitoring and control system based on artificial intelligence. To be implemented, the system will be modeled and tested on the Proteus software to simulate the hardware of sensor, microcontrollers, and actuators and Python programming language will be used to implement algorithms, data analysis, and machine learning. The simulation tools help make it cost-effective, allow testing a variety of scenarios, and verify it prior to physical implementation. Lastly, analysis of performance will be done by simulation experiments. The system would be put through different conditions of the environment. To confirm the success of the proposed AI-based greenhouse control system, the experimental results will be compared with the measurements of the baseline values at the beginning of the system characterization.

2.2 Data Acquisition

Data of the greenhouse condition was collected using the setup in figure 3.2. The plants considered are pepper and tomatoes. To account for temporal variability, measurements were taken at one hour intervals each day for 24 hours. Seasonal variations were captured by conducting data collection campaigns during both the dry season (harmattan, November–February) and the rainy season (April–July). The year of data collection is 2023- 2024. After the data collection, the overall daily hourly average of the environmental condition across season was compared with the ideal data and then used for analysis. Alongside environmental and soil data, crop growth parameters such as plant height, leaf area, flowering time, and yield per plant were recorded. Plant height was measured with a meter rule, leaf area was estimated using a leaf area meter, and yield was quantified using a digital weighing balance. The selection of these parameters and instruments was guided by their relevance to the physiology of tomato and pepper crops. By considering seasonal variations, the data collection framework ensured a very good characterization of the greenhouse farm. The collected data are reported in Table 1 and 2.

Table 1: Overall average daily hourly greenhouse condition for Hamathan Season

Timestamp (GMT) Houly	Temperature_^{0}C	Humidity_%	Soil_Moisture_%	PAR_umol_m2_s
0:01	20.35	45.15	27.37	147
1:00	21.63	42.79	30.05	152
2:00	26.39	55.39	12.8	127

3:00	21.51	40.68	17.88	144
4:00	20.42	59.13	14.87	155
5:00	18.7	34.66	24.97	164
6:00	20.66	55.24	26.61	132
7:00	18.87	47.38	25.86	74
8:00	22.79	56.42	27.3	87
9:00	24.16	45.82	29.44	154
10:00	22.63	45.97	20.52	104
11:00	18.63	48.13	31.78	123
12:00	19.2	47.84	21.93	263
13:00	21.16	25.81	30.21	128
14:00	24.62	62.87	33.11	189
15:00	24.69	49.15	26.64	161
16:00	20.97	47.51	23.36	107
17:00	23.38	52.74	23.54	258
18:00	18.71	49.15	21.67	149
19:00	17.62	42.58	24.63	119
20:00	21.81	43.45	24.6	148
21:00	25.2	43.4	24.96	138
22:00	18.03	33.32	24.31	110
23:00	22.65	30.09	22.17	097
AVG	21.44917	46.02792	24.6075	142.9167
Ideal	25.99979	74.99872	58.66571	193.1798
Deviation (%)	17.50	38.66	58.06	26.05

Table 1 presents the results of the greenhouse condition characterized considering temperature, humidity, light, and soil pH as the main environmental variables. From the results, it was observed that the average overall temperature at the testbed is 21.44917 °C, which is about 17.5% lower than the ideal benchmark value of 25.99979 °C. Similarly, the average humidity was 46.02792%, representing a deviation of approximately 38.6% from the required 74.99872%. Soil moisture also averaged 24.6075%, which is about 58.1% below the optimal 58.66571%. In terms of PAR, the greenhouse recorded 142.9167 µmol/m²/s, about 26.0% lower than the ideal value of 193.1798 µmol/m²/s. These significant deviations highlight that the prevailing microclimatic conditions are far from optimal for sustaining healthy tomato and pepper plant growth and productivity. The current manual monitoring methods at the farm are inadequate for capturing such fluctuations in real time, especially when multiple variables interact dynamically. Therefore, the findings underscore the critical need for an intelligent greenhouse monitoring and control system driven by Artificial Intelligence. Table 2 presents the overall average daily hourly greenhouse condition for rainy season.

Table 2: Overall average daily hourly greenhouse condition for Rainy Season

Timestamp (GMT) Hourly	Temperature_^{0}C	Humidity_%	Soil_Moisture_%	PAR_umol_m2_s
0:01	28.02	67.91	38.2	136
1:00	29.28	75.84	57.36	116
2:00	20.36	55.5	36.15	120
3:00	23.79	70.06	57.51	148
4:00	29.02	55.82	30.91	120

5:00	22.67	53.39	45.23	227
6:00	27.91	88.61	60.09	216
7:00	26.08	70.66	53.72	053
8:00	24.55	76.96	52.64	118
9:00	24.29	66.97	37.98	177
10:00	26.49	71.9	49.61	132
11:00	28.64	60.57	47.43	103
12:00	32.03	71.41	30.85	162
13:00	25.77	75.29	39.47	134
14:00	24.6	58.89	44.59	149
15:00	27.3	71.46	41.29	277
16:00	26.48	69	43.37	154
17:00	23.79	50.63	41.16	198
18:00	26.49	71.02	35.95	160
19:00	29.36	61.09	36.5	106
20:00	29.78	54.37	40.77	149
21:00	25.33	59.36	47.46	180
22:00	26.51	80.18	66.31	171
23:00	33.52	79.4	49.41	133
AVG	26.7525	67.34542	45.165	151.625
ideal	25.99979	74.99872	58.66571	193.1798
Deviation (%)	2.90	10.20	22.99	21.51

The analysis of the rainy season greenhouse conditions in Table 2 reveals that the average temperature recorded was 26.75 °C, which is slightly higher than the ideal benchmark of 25.99 °C, giving a deviation of about 2.90%. This indicates that the temperature levels are within an acceptable range for plant growth, although minor fluctuations may still impact temperature-sensitive crops. The average relative humidity was 67.35%, which is lower than the ideal 74.99%, showing a 10.20% deviation. While the value falls within a moderately suitable range, the reduction in humidity could lead to increased evapotranspiration and stress for crops requiring high moisture content.

Soil moisture during the rainy season averaged 45.17%, against the recommended 58.67%, representing a significant 22.99% shortfall. Despite rainfall, this suggests that water distribution within the greenhouse soil was uneven, which may affect root water uptake and overall plant physiology. For PAR, the greenhouse recorded 151.63 µmol/m²/s, compared to the ideal 193.18 µmol/m²/s, translating to a 21.51% deficit. This reduced light intensity, common during cloudy and rainy periods, could negatively affect photosynthesis efficiency and crop productivity.In summary, while temperature levels during the rainy season are relatively close to the ideal, the considerable deviations in soil moisture, humidity, and light intensity highlight the challenges of maintaining optimal microclimatic conditions. These findings emphasize the necessity of deploying an AI-driven intelligent monitoring and control system capable of dynamically regulating irrigation, ventilation, and supplemental lighting. Such a system would ensure that even during periods of environmental variability, the greenhouse maintains stable and crop-friendly conditions for improved yield and resource efficiency.

3. DEVELOPMENT OF THE INTELLIGENT EVENT TRIGGERING CONTROL SYSTEM FOR REAL-TIME MONITORING AND PREDICTION OF GREENHOUSE CONDITION USING ANN

The intelligent event-triggering control system is designed for monitoring and prediction of dynamic changes in greenhouse conditions in real time. Its development is based on the integration of an Artificial Neural Network (ANN) model for prediction, and generation of control actions. The following subsections describe the development stages in detail.

3.1 ANN Model Design

The ANN model was structured to capture the nonlinear relationships between environmental parameters and greenhouse events. The input layer consisted of sensor data representing temperature, humidity, soil pH, light intensity, and soil moisture. The hidden layers employed nonlinear activation functions (ReLU and Sigmoid) to learn complex interactions between these variables. The output layer generated classification results corresponding to environmental condition in the farm. The mathematical model of ANN neuron is presented as Algorithm 1

Algorithm 1: Python code of the ANN model

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
# Define ANN model
model = keras.Sequential([
    layers.Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    layers.Dense(32, activation='relu'),
    layers.Dense(1)  # regression output
])
# Compile
model.compile(optimizer='adam', loss='mse', metrics=['mae'])
# Train
history = model.fit(X_train, y_train,
                    validation_data=(X_test, y_test),
                    epochs=50, batch_size=32, verbose=1)
```

3.2 Training Dataset and Preparation

The training dataset was collected from the testbed considering the period of 2020 to 2024 with daily information that characterized the greenhouse. The sample size of the data collected is 35064 records for tomato and pepper plants. Each record consisted of input features (environmental variables) and labeled outputs (control events). Data augmentation and normalization were applied to improve generalization and prevent bias from uneven event distributions using synthetic monitoring over sampling approach. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets for effective model development. Algorithm 2 presents sample results of training python code of the proposed model.

Algorithm 2: Codes of the data importation and preparation

```
from google.colab import files
import pandas as pd

# Upload CSV file
uploaded = files.upload()

# Load into pandas DataFrame
file_name = list(uploaded.keys())[0]   # get uploaded filename
df = pd.read_csv(file_name)

print("Data shape:", df.shape)
print("Columns:", df.columns.tolist())

# Preview
df.head()
```

Data preparation codes

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Noramlization and augmentation
X = df[["temperature_C", "relative_humidity_pct", "PAR_umol_m2_s",
"N_pct"]]
y = df["daily_yield_kg"]
```

```
# Split dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Scale features for ANN
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

3.3 ANN Training and greenhouse condition prediction model generation

Model training was conducted using the backpropagation algorithm with an adaptive learning rate optimizer (Adam). The loss function used was categorical cross-entropy, suitable for multi-class event prediction. Early stopping and dropout techniques were incorporated to prevent over fitting and ensure generalization across unseen data. Performance metrics such as mean square error, loss and accuracy were used to evaluate the model's predictive ability. Once the ANN was trained, a greenhouse condition prediction model was generated. This control model established a closed-loop system where real-time sensor data was continuously fed to the ANN, and actuator responses were automatically executed without human intervention. Model validation involved comparing ANN-predicted events with actual environmental conditions and control responses. Performance was benchmarked against ideal data collected to demonstrate improvements in efficiency, adaptability, and resource conservation. Figure 1 presents flow chart of the greenhouse condition prediction model.

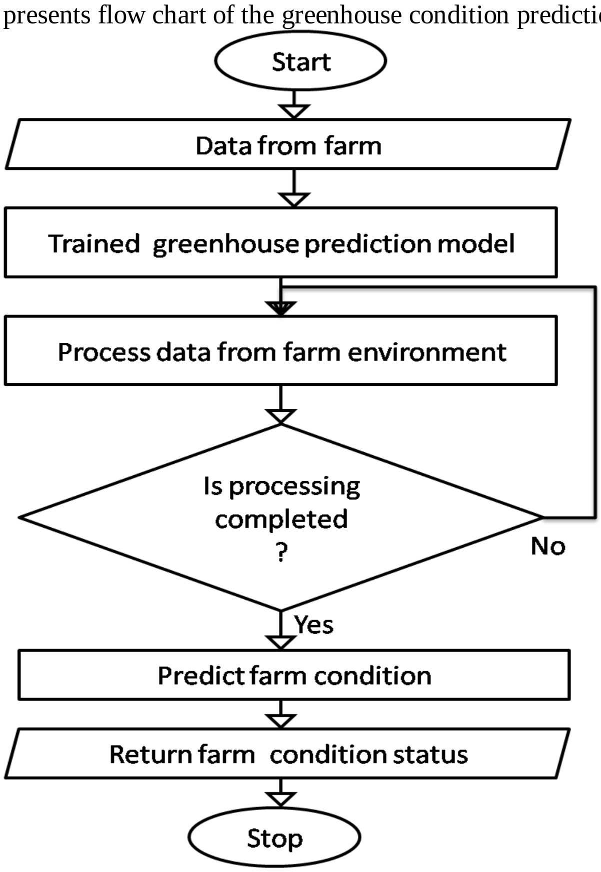


Figure 1: Flowchart of the greenhouse condition prediction model

4. RESULT OF TRAINING DATA ANALYSIS

Historical data of the testbed was collected over four years, 2021 to 2024 and the reason as to train neural network and generate greenhouse condition prediction model. The collected data was analyzed across using diagonal plots in Figure 2.

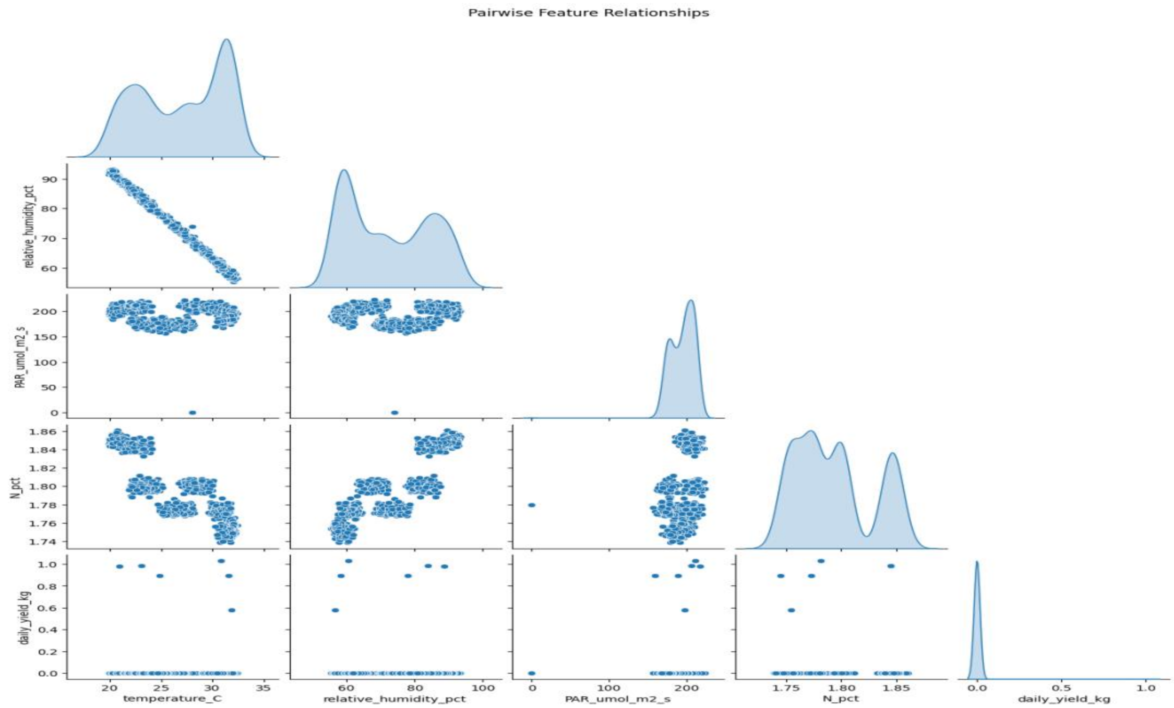


Figure 2: Diagonal and off diagonal scatter plots of the greenhouse data

This plot in Figure 2 shows the pairwise relationships among the main variables: temperature (°C), relative humidity (%), PAR (µmol/m²/s), N content (%), and daily yield (kg). The plot gives the distribution of each variable individually. For example, temperature shows a multi-modal distribution, meaning the greenhouse experienced different operating temperature ranges which is due to seasonal variations). Similarly, humidity has two clear clusters, indicating dry and wet periods. This clustering is important because plants respond differently in these ranges, and AI-based monitoring can learn seasonal patterns for better prediction.

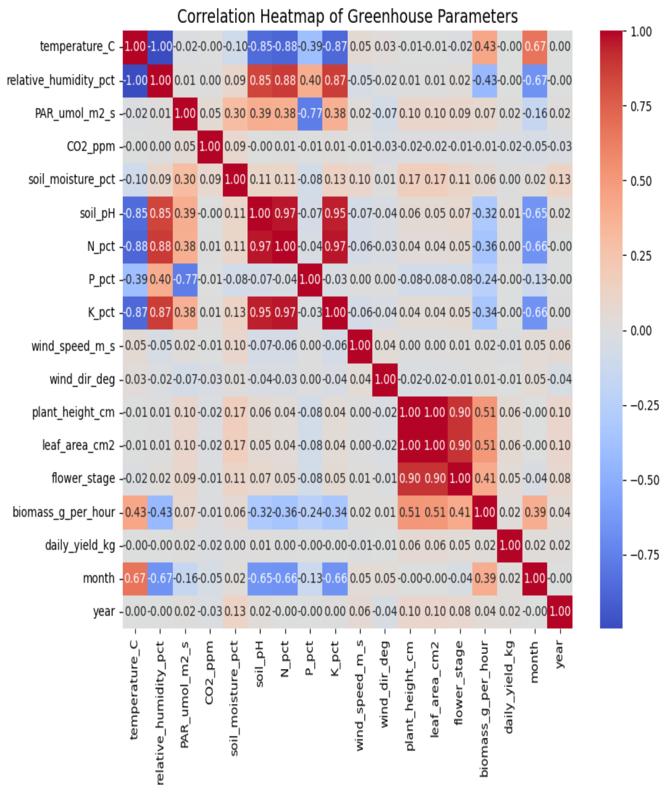
The Off-diagonal scatter plots reveal correlations among variables in the dataset. For instance, temperature and humidity show a strong negative relationship as temperature increases, humidity tends to drop. This is a well-known greenhouse challenge, since higher temperature drives evapotranspiration and reduces relative humidity, stressing crops. Similarly, PAR vs. yield shows scattered low yield values, suggesting that even under good light, yield does not always increase and the reason was due to limiting factors like soil moisture or nutrient deficiencies.

This matrix reveals that no single factor determines yield rather, yield emerges from the complex interaction of temperature, humidity, soil moisture, and nutrient availability. Figure 3 presents the correlation heatmap. The figure maps out the relationships between all greenhouse parameters, with each square showing how strongly two factors are related, with red meaning strong positive correlation and blue meaning strong negative correlation. The diagonal matrix value of 1 indicates that perfect fit of the data variables, which is good and implied that the dataset is perfectly structured and well suitable to train machine learning algorithm or the prediction of greenhouse condition.

Figure 3 showed the correlation heatmap of the dataset, while Figure 4 presents the distribution of greenhouse variables. This set of histograms shows how often different values of temperature, humidity, light, soil moisture, nutrients, and yield occurred in the greenhouse. Each plot has bars (frequency) with a smooth curve on top showing the overall shape. In the results, with distribution of temperature, most values cluster around 30–32 °C, higher than the ideal range. This suggests overheating is a common issue that must be managed to protect plants.

The humidity distribution spread between 55% and 90%, showing two groups one during the dry season (lower humidity) and one during the rainy season (higher humidity). Humidity affects how plants lose water, so it's a key factor for irrigation planning.

For the Light (PAR) distribution, most values are between 150–200 µmol/m²/s, but often below the ideal. This shows that cloudy weather reduces available light, and supplemental lighting may be needed. Soil moisture distribution clustered around 55–60%, showing irrigation kept soil relatively wet, but there may still be periods of under- or over-watering. Proper balance is essential for root health. Nutrient distribution (N%) shows peaks at different points, meaning nutrient supply varies with fertilizer applications. Monitoring this ensures crops always have the right nutrients at the right time; while daily yield distribution values are close to zero, with very few higher yields.



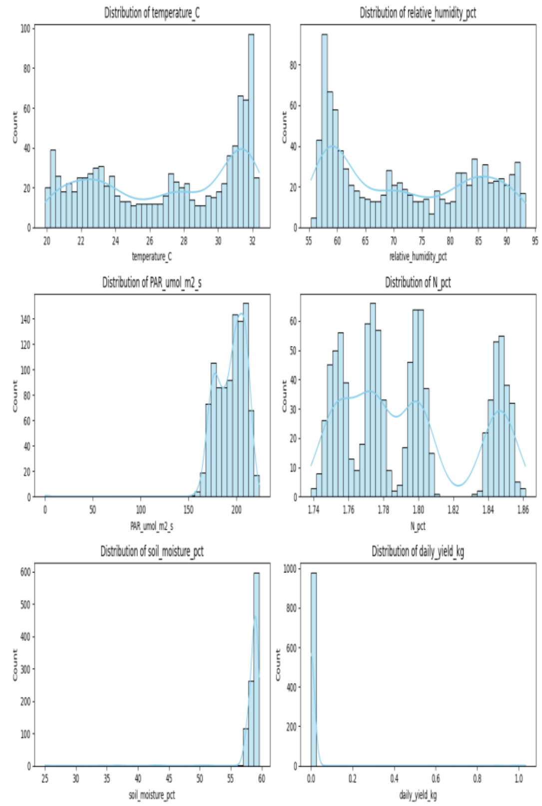


Figure 3: The Correlation Heatmap Analysis Figure 4: Distribution analysis of the training dataset

This suggests that despite reasonable environmental conditions, plants are not achieving their potential. This makes it clear that better control and optimization of all factors together are necessary. These distributions show that the greenhouse often runs outside of the ideal range for several factors. AI systems can help by detecting when conditions drift away from the ideal and adjusting in real time, ensuring plants always grow in their “comfort zone.”

The three sets of diagrams collectively reveal that greenhouse productivity is influenced by the dynamic interplay between temperature, humidity, light, water, and nutrients. While some conditions (like soil moisture) appear moderately controlled, others (like temperature, humidity, and light) show frequent deviations from ideal thresholds. Yield remains low and inconsistent, reflecting the inability of manual or traditional control methods to optimize multiple variables simultaneously. By integrating sensor data, recognizing complex correlations, and predicting yield-limiting conditions, such a system can automatically regulate ventilation, irrigation, and lighting. This ensures crops remain within their physiological comfort zone, ultimately improving growth, reducing resource waste, and maximizing productivity.

4.1 Result of ANN Training and greenhouse condition prediction model generation

Training of the neural network produced the greenhouse environmental condition prediction model. The model performance was evaluated considering accuracy, loss and mean absolute error. The results of the training process were reported in the Figure 5 for accuracy and loss, while Figure 6 presents the mean absolute error performance.

The results across several epochs showed consistent accuracy value of 1, which is very good and implied that out model was able to correctly predict the environmental condition at the greenhouse with 100% success rate. The reason was due to the superior performance of the neural network and also careful preparation of the training dataset. The training loss recorded 2.6657e-04, while the validation loss reported 2.0761e-04. The MAE recorded 0.028, which is 2.8% deviation error. These loss and error values are very tolerable and implied that our model was able to correctly predict greenhouse condition with limited error. The coefficient determination value reported 0.9719 which approximates in percentage 97.2% for correctly predicting greenhouse environmental variables. These results makes the ANN based greenhouse condition prediction model suitable for real-time monitoring of the testbed.

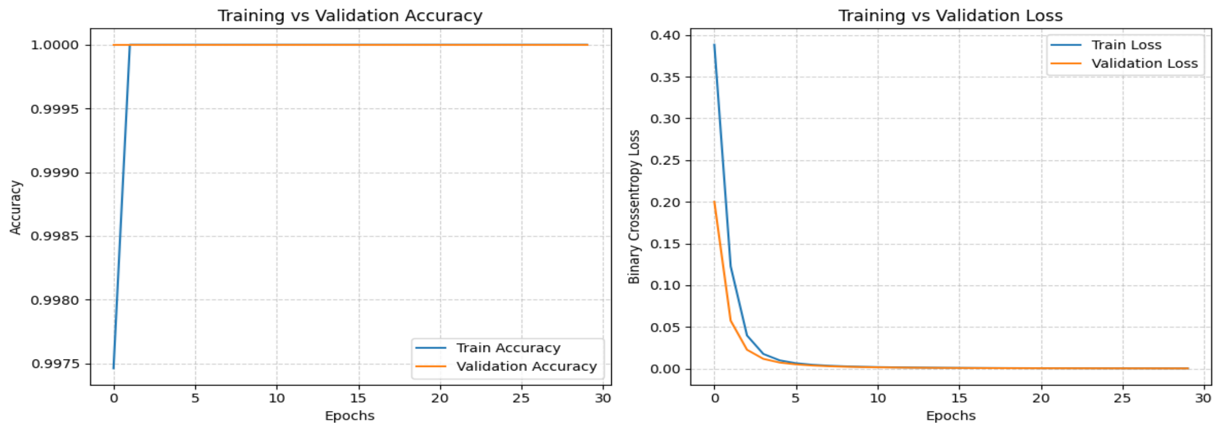


Figure 5: Result of ANN training

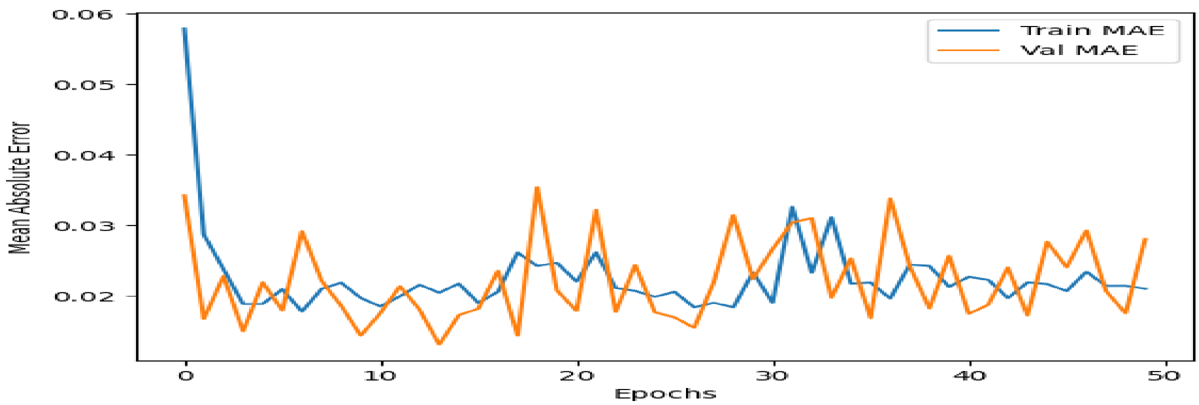


Figure 6: Result of the MAE for the ANN training

4.2 Result of System Validation

In the system validation, we compared the performance of the characterized system, the new system against the ideal benchmark results. The validation process aimed to confirm whether the integration of AIETCS reliably maintain greenhouse parameters such as temperature, humidity, soil moisture, and PAR within acceptable thresholds. By analyzing deviations across the rainy and harmattan seasons, the results provided quantitative evidence of the system's stability, adaptability, and overall effectiveness in aligning environmental conditions with optimal plant growth requirements.

Table 3: Comparative greenhouse performance during Rainy Season

Time Hour GMT	Characterized				New				Ideal			
	T C^o	H%	Soil Moisture %	PAR **umol_m2_s**	T C^o	H%	Soil Moisture %	PAR **umol_m2_s**	T C^o	H%	Soil Moisture %	PAR **umol_m2_s**
0:01	20.35	45.15	27.37	20.35	25.25	72.82	57.23	178.3	26.00	75.00	58.67	193.18
1:00	21.63	42.79	30.05	21.63	26.38	74.9	55.17	193.49	26.00	75.00	58.67	193.18
2:00	26.39	55.39	12.8	26.39	25.83	70.64	59.64	191.46	26.00	75.00	58.67	193.18
3:00	21.51	40.68	17.88	21.51	25.49	72.93	58.53	191.87	26.00	75.00	58.67	193.18
4:00	20.42	59.13	14.87	20.42	24.38	73.5	59.47	192.67	26.00	75.00	58.67	193.18
5:00	18.7	34.66	24.97	18.7	24.38	69.52	59.21	179.59	26.00	75.00	58.67	193.18
6:00	20.66	55.24	26.61	20.66	24.13	73.61	57.52	184.92	26.00	75.00	58.67	193.18
7:00	18.87	47.38	25.86	18.87	26.17	70.42	59.37	180.37	26.00	75.00	58.67	193.18

8:00	22.79	56.42	27.3	22.79	25.5	69.66	54.62	194.39	26.00	75.00	58.67	193.18
9:00	24.16	45.82	29.44	24.16	25.77	76.09	55.23	189.89	26.00	75.00	58.67	193.18
10:00	22.63	45.97	20.52	22.63	24.04	76.21	54.37	184.41	26.00	75.00	58.67	193.18
11:00	18.63	48.13	31.78	18.63	26.43	75.07	55.97	179.39	26.00	75.00	58.67	193.18
12:00	19.2	47.84	21.93	19.2	26.09	71.4	56.33	184.03	26.00	75.00	58.67	193.18
13:00	21.16	25.81	30.21	21.16	24.52	69.89	55.66	184.3	26.00	75.00	58.67	193.18
14:00	24.62	62.87	33.11	24.62	24.44	74.17	58.84	191.88	26.00	75.00	58.67	193.18
15:00	24.69	49.15	26.64	24.69	24.45	72.39	56.15	190.16	26.00	75.00	58.67	193.18
16:00	20.97	47.51	23.36	20.97	24.75	70.07	55.72	194.84	26.00	75.00	58.67	193.18
17:00	23.38	52.74	23.54	23.38	25.31	72.79	57.21	187.06	26.00	75.00	58.67	193.18
18:00	18.71	49.15	21.67	18.71	25.07	69.43	54.92	180.44	26.00	75.00	58.67	193.18
19:00	17.62	42.58	24.63	17.62	24.72	75.8	58.69	191.58	26.00	75.00	58.67	193.18
20:00	21.81	43.45	24.6	21.81	25.53	71.07	54.54	192.47	26.00	75.00	58.67	193.18
21:00	25.2	43.4	24.96	25.2	24.34	74.01	59.74	188.73	26.00	75.00	58.67	193.18
22:00	18.03	33.32	24.31	18.03	24.72	71.45	58.52	192.66	26.00	75.00	58.67	193.18
23:00	22.65	30.09	22.17	22.65	24.91	72.97	55.25	187.46	26.00	75.00	58.67	193.18
AVG	21.44	46.027	24.60	21.44	25.09	72.52	57	187.76	26.00	75.00	58.67	193.18
Ideal	25.99	74.99	58.66	25.99	26	75	58.67	193.18	26.00	75.00	58.67	193.18
ξ(%)	17.50	38.66	58.06	17.50	3.48	3.3	2.85	2.8	26.00	75.00	58.67	193.18

The comparative results presented in Table 3 clearly demonstrate the superiority of the newly developed greenhouse control system, which integrates ANN-based greenhouse condition prediction model with the event-triggered control strategy. Under the rainy season condition, the old characterized system recorded large deviations from the ideal setpoints, with temperature, humidity, soil moisture (pH proxy), and PAR deviating by 17.50%, 38.66%, 58.06%, and 17.50%.

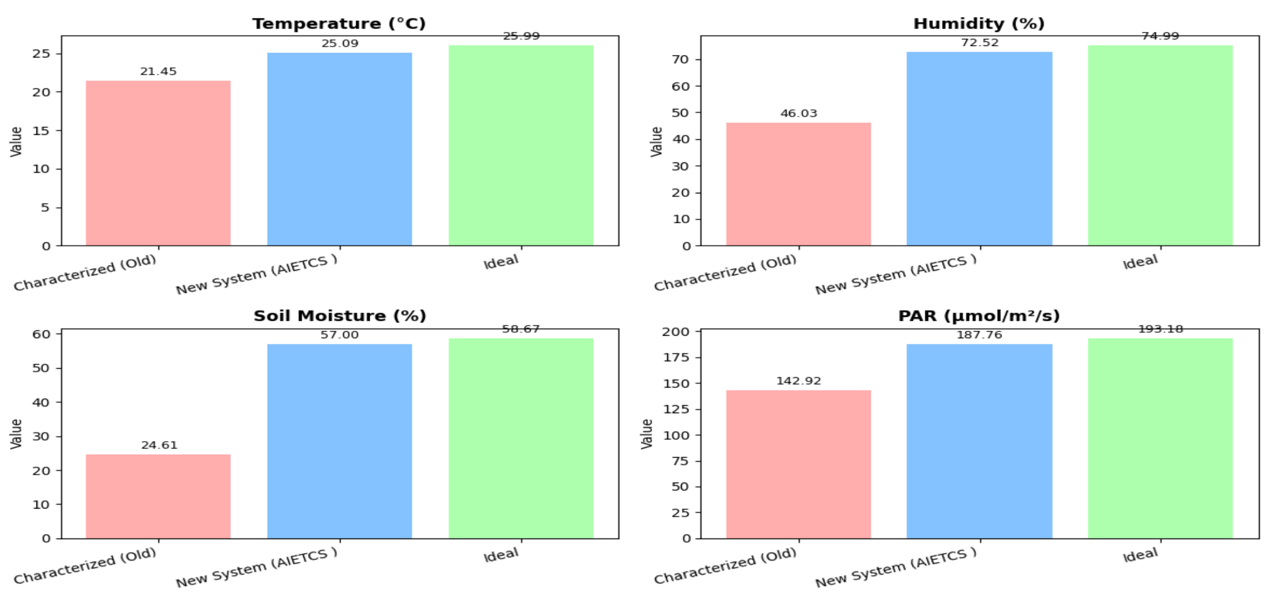


Figure 7: Comparative greenhouse performance in rainy season

The result in Figure 7 for the old system reflects poor stability and limited adaptability to environmental variability. In contrast, the new system which is AIETCS based maintained the same parameters at deviations as low as 3.48%,

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3.30%, 2.85%, and 2.80%, showing a dramatic reduction in error margins and a much closer alignment with the ideal conditions. This improvement can be attributed to the ANN's ability to learn complex nonlinear relationships between environmental inputs and plant growth requirements, while the event-triggered control ensures timely corrective actions only when deviations exceed thresholds, minimizing unnecessary energy use. Together, these features provide a self-adaptive, intelligent, and resource-efficient regulation mechanism. The system not only ensures stable microclimatic conditions but also justifies its development by improving productivity, reducing resource wastage, and guaranteeing resilience against seasonal fluctuations, thereby addressing the limitations of the old control approach.

Table 4: Comparative greenhouse performance during Hamathan Season

Time Hour GMT	Characterized				New				Ideal			
	T C^o	H%	Soil Moisture %	PAR **umol_m2_s**	T C^o	H%	Soil Moisture %	PAR **umol_m2_s**	T C^o	H%	Soil Moisture %	PAR **umol_m2_s**
0:01	28.02	67.91	38.2	136	24.93	72.50	57.23	178.30	26.00	75.00	58.67	193.18
1:00	29.28	75.84	57.36	116	26.38	74.90	55.17	193.49	26.00	75.00	58.67	193.18
2:00	20.36	55.5	36.15	120	25.83	70.64	59.64	191.46	26.00	75.00	58.67	193.18
3:00	23.79	70.06	57.51	148	25.49	72.93	58.53	191.87	26.00	75.00	58.67	193.18
4:00	29.02	55.82	30.91	120	24.38	73.50	59.47	192.67	26.00	75.00	58.67	193.18
5:00	22.67	53.39	45.23	227	24.38	69.52	59.21	179.59	26.00	75.00	58.67	193.18
6:00	27.91	88.61	60.09	216	24.13	73.61	57.52	184.92	26.00	75.00	58.67	193.18
7:00	26.08	70.66	53.72	053	26.17	70.42	59.37	180.37	26.00	75.00	58.67	193.18
8:00	24.55	76.96	52.64	118	25.50	69.66	54.62	194.39	26.00	75.00	58.67	193.18
9:00	24.29	66.97	37.98	177	25.77	76.09	55.23	189.89	26.00	75.00	58.67	193.18
10:00	26.49	71.9	49.61	132	24.04	76.21	54.37	184.41	26.00	75.00	58.67	193.18
11:00	28.64	60.57	47.43	103	26.43	75.07	55.97	179.39	26.00	75.00	58.67	193.18
12:00	32.03	71.41	30.85	162	26.09	71.40	56.33	184.03	26.00	75.00	58.67	193.18
13:00	25.77	75.29	39.47	134	24.52	69.89	55.66	184.30	26.00	75.00	58.67	193.18
14:00	24.6	58.89	44.59	149	24.44	74.17	58.84	191.88	26.00	75.00	58.67	193.18
15:00	27.3	71.46	41.29	277	24.45	72.39	56.15	190.16	26.00	75.00	58.67	193.18
16:00	26.48	69	43.37	154	24.75	70.07	55.72	194.84	26.00	75.00	58.67	193.18
17:00	23.79	50.63	41.16	198	25.31	72.79	57.21	187.06	26.00	75.00	58.67	193.18
18:00	26.49	71.02	35.95	160	25.07	69.43	54.92	180.44	26.00	75.00	58.67	193.18
19:00	29.36	61.09	36.5	106	24.72	75.80	58.69	191.58	26.00	75.00	58.67	193.18
20:00	29.78	54.37	40.77	149	25.53	71.07	54.54	192.47	26.00	75.00	58.67	193.18
21:00	25.33	59.36	47.46	180	24.34	74.01	59.74	188.73	26.00	75.00	58.67	193.18
22:00	26.51	80.18	66.31	171	24.72	71.45	58.52	192.66	26.00	75.00	58.67	193.18
23:00	33.52	79.4	49.41	133	24.91	72.97	55.25	187.46	26.00	75.00	58.67	193.18
AVG	26.7525	67.34542	45.165	151.625	25.09	72.52	57.00	187.76	26.00	75.00	58.67	193.18
Ideal	25.99979	74.99872	58.66571	193.1798	26.00	75.00	58.67	193.18	26.00	75.00	58.67	193.18
ξ(%)	2.90	10.20	22.99	21.51	3.48	3.30	2.85	2.80	26.00	75.00	58.67	193.18

The comparative greenhouse performance in Table 4 during the Harmattan season highlights the effectiveness of the new ANN predictive control system for greenhouse and event-triggered control system. Under the characterized (old) system, the greenhouse conditions deviated significantly from the ideal, with temperature, humidity, soil moisture (pH proxy), and PAR showing errors of 2.90%, 10.20%, 22.99%, and 21.51%, respectively as shown in Figure 8.

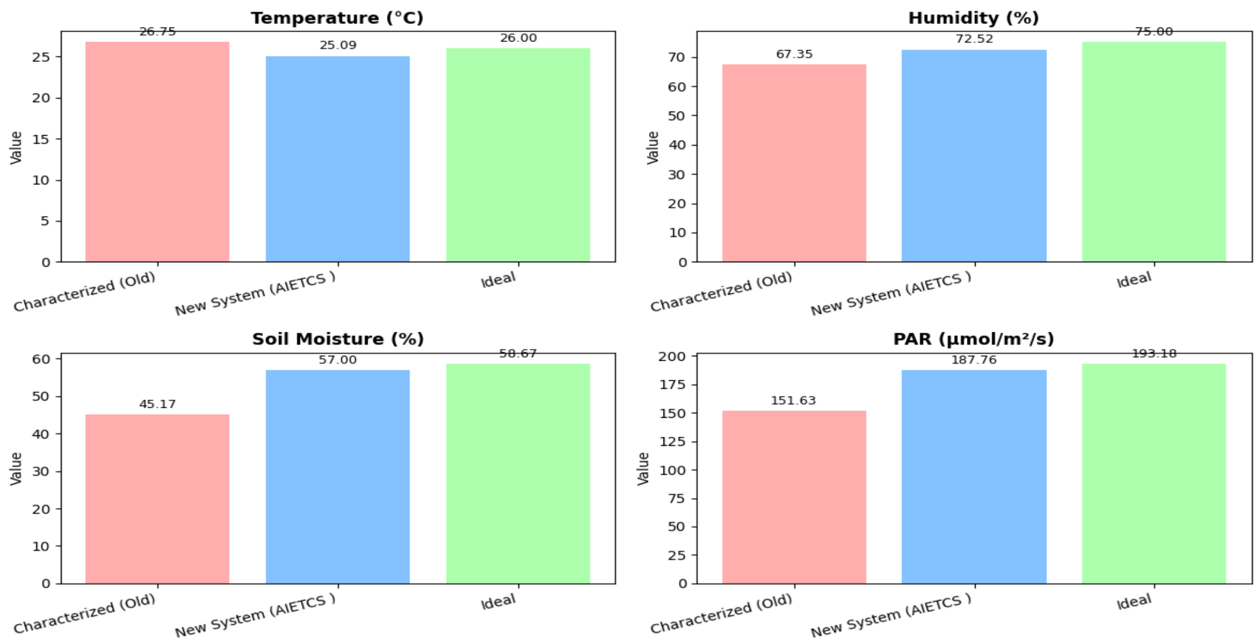

Figure 8: Comparative greenhouse performance in Hamathan

These large deviations in Figure 8 reflect the challenges of Harmattan, where dry winds, dust, and fluctuating radiation levels make environmental regulation difficult. In contrast, the new system achieved much tighter control, recording deviations of only 3.48% for temperature, 3.30% for humidity, 2.85% for soil moisture, and 2.80% for PAR. This shows that while the old system struggled particularly with humidity, soil moisture, and light regulation, the ANN-based approach minimized error margins across all parameters. The improvement can be attributed to the ANN's capacity to model nonlinear seasonal dynamics and the event-control mechanism's ability to trigger rapid adjustments when thresholds are exceeded. Overall, the new system demonstrates superior adaptability to Harmattan stress, ensuring stable microclimate conditions that promote plant growth, reduce risk of stress or disease, and optimize input efficiency despite the harsh seasonal environment.

Overall, the comparative results across the Rainy and Harmattan seasons confirm that the new ANN and event-triggered control system ensures consistent greenhouse performance under contrasting climatic conditions. During the Rainy season, where excess humidity and reduced solar radiation are the main challenges, the system-maintained deviations within 3.48%, 3.30%, 2.85%, and 2.80% for temperature, humidity, soil moisture, and PAR, respectively, preventing excessive moisture buildup while sustaining optimal light and temperature for growth. In the Harmattan season, characterized by dry winds, low humidity, and high radiation fluctuations, the system again kept deviations low at 3.48%, 3.30%, 2.85%, and 2.80%, overcoming the limitations of the old system, which showed far higher error levels in humidity, soil moisture, and PAR. This consistency across both extremes demonstrates that the new intelligent control model is not only adaptive and resilient but also reliable in stabilizing the greenhouse microclimate year-round, ensuring crop health and resource efficiency regardless of external seasonal stresses.

5. CONCLUSION

The paper aimed at designing and creating an AIETCS to monitor and predict greenhouse using an ANN. This was driven by the fact that there has been a constant inconsistency between ideal greenhouse environmental conditions as documented in literature and the volatile conditions that have been experienced in field practice, which in most cases, lower crop yield and resource efficiency. The quantitative simulation-based approach was taken. Initial characterization of greenhouse was done to determine the baseline conditions and optimal set points of the important variables: air temperature, relative humidity, soil moisture, photosynthetically active radiation (PAR) and soil nutrients. Greenhouse operations were surveyed during the rainy and the Harmattan seasons, which recorded time variation of the environmental state and crop growth performance.

The suggested AIETCS architecture comprised the sensor data acquisition, pre-processing, ANN-based prediction, event-triggered logic, and actuator control. ANN was trained on pre-processed (scaling, imputation, balancing) multi-season greenhouse data, the data were divided into training (70%), validation (15%), and testing (15%) sets. The ANN was able to identify the nonlinearities between the environmental variables and the greenhouse outcome. Low validation loss, absolute error of mean of about 2.8% and coefficient of determination (R2R2R2) of 0.97, all reflect high predictive capability of the training. The three setups that were compared during system validation were: (i) baseline that defined greenhouse, (ii) AIETCS using ANN prediction, and (iii) literature based ideal benchmarks. Findings established that the deviations under ideal conditions were high (up to 58% of soil moisture and approximately 38% of relative humidity) but the AIETCS revealed a steady deviation of 3350 (3-35) of all the variables in either season. This advancement came in the form of more predictable crop growing conditions, lower actuation rate, and less waste of resources.

To sum up, the created ANN-based event-driven control system demonstrated greatly enhanced greenhouse stability and prediction accuracy in comparison with the baseline operations. This feature is allowed by the inclusion of AI in the control of greenhouses, which allows the active regulation of important variables to maintain conditions as close as possible with the minimum use of resources. This study therefore contributes a scalable, intelligent control framework that enhances agricultural productivity, resource efficiency, and sustainability.

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