



AloT-Based Energy-Efficient Temperature Regulation for Closed-System Greenhouses in Tropical Climates Using Machine Learning-Based Classification Control

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ABSTRACT

Closed-system greenhouses have gained increasing popularity due to their ability to precisely control environmental conditions, support vertical farming, and enhance crop yield in limited spaces. However, maintaining optimal temperature control under continuously changing outdoor weather conditions while improving energy efficiency remains a significant challenge. This study presents the development of an Artificial Intelligence (AI) and Internet of Things (IoT)-based architecture incorporating energy management for temperature regulation in a closed-system greenhouse using a machine learning-based classification control decision approach. IoT sensors continuously collect environmental and electrical parameters, including indoor and outdoor temperature, humidity, voltage, current, and power consumption, and transmit the data to a cloud platform for monitoring and analysis. Machine learning classification models were trained offline in MATLAB/Simulink and employed to determine air-conditioning activation for energy-efficient greenhouse operation. Three models—Quadratic Support Vector Machine (QSVM), Cubic Support Vector Machine (CSVM), and Ensemble Bagged Trees (BT)—were trained and evaluated. Experimental results show that the BT model is suitable for real greenhouse deployment, achieving 98.46% accuracy comparable to QSVM with lower computational complexity, while its lightweight nature suits cloud platforms with limited communication resources. Furthermore, real-world implementation testing conducted over a two-day period demonstrates that the BT-based control system reduces energy consumption by approximately 20.54% compared with a conventional system without AI-based control. This approach has the potential to reduce energy consumption in closed-system greenhouses; however, it would require adjustments in data collection and model configuration to account for differing plant physiological characteristics.

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1. INTRODUCTION

Greenhouse farming in hot and humid tropical climates plays a key role in maintaining stable crop production under challenging environmental conditions. Among various environmental factors, temperature control directly affects vegetable growth and quality, particularly during hot seasons. Temperature regulation demand during these periods makes

air-conditioning systems the major source of energy consumption. Therefore, maintaining optimal greenhouse temperatures while minimizing unnecessary energy use is essential for reducing production costs and ensuring consistent crop quality.

Closed-system greenhouses face additional challenges in tropical regions such as Thailand, where ambient temperatures remain high throughout the year and relative humidity varies substantially. According

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to data from the Thai Meteorological Department, average maximum temperatures across most regions range between 32–34 °C during September and October [1]. These conditions force cooling systems to operate intensively, leading to high and often unavoidable energy consumption. To address these challenges, the integration of Artificial Intelligence (AI) with the Internet of Things (IoT), commonly referred to as Artificial Intelligence of Things (AIoT) has attracted increasing attention in agricultural applications [2], [3]. AIoT technologies have been widely explored to support environmental monitoring and smart greenhouse management through distributed sensing and cloud-based data processing platforms [4], [5], while comprehensive reviews have summarized various environmental control strategies and modeling approaches for modern agricultural greenhouses [6]. Furthermore, artificial intelligence techniques have been applied for energy consumption forecasting, temperature prediction, and control optimization in greenhouse systems [7], [8], [9], [10], while renewable-energy-based approaches have also been investigated to improve overall energy efficiency in greenhouse operations [11].

Extensive research has been conducted on various greenhouse environmental control approaches, including thermal modeling, experimental validation, and intelligent control algorithms. An adaptive neuro-fuzzy inference system (ANFIS) was designed and analyzed for greenhouse temperature control to improve regulation performance under varying environmental conditions [12]. Dynamic thermal models for greenhouse temperature prediction using energy balance equations and MATLAB/Simulink have been developed and experimentally validated for different greenhouse types, with emphasis on environmental and thermal behavior analysis rather than control strategies [13], [14]. Intelligent climate control algorithms for greenhouse systems were investigated by comparing PID, fuzzy logic, and PSO-based fuzzy controllers for temperature and humidity regulation [15]. A hybrid control approach combining on-off, PID, and Fuzzy-PI controllers was implemented for greenhouse microclimate regulation using a hardware-in-the-loop platform [16]. A fuzzy logic controller was implemented for greenhouse temperature regulation to improve environmental control performance [17]. A data-driven robust model predictive control (MPC) approach was developed for greenhouse temperature regulation and energy utilization assessment to improve control performance and energy efficiency [18]. IoT and reinforcement learning technologies were integrated for greenhouse climate control to enhance operational efficiency and energy management [19]. A hybrid CNN-LSTM framework was developed for predicting fan actuator states in smart greenhouses to support intelligent climate control and decision-making [20]. A machine learning-based intelligent

actuator control system integrated with sensor data was developed for smart agriculture to improve automated decision-making and environmental control performance [21]. However, these existing approaches remain challenging to implement in practical applications, particularly for low-cost systems operating under rapidly changing environmental conditions. Conventional PID and fuzzy controllers often require careful parameter tuning or complex rule design, while MPC and neural network-based approaches typically require high computational resources, extensive training data, and increased implementation complexity. In contrast, data-driven approaches, particularly machine learning-based methods for control decision-making, provide greater flexibility by reducing reliance on explicit mathematical models and enabling more effective handling of nonlinear system behavior.

Accordingly, this research proposes a framework for energy management in low-cost closed-system greenhouses by integrating sensor-based data acquisition, data preprocessing for machine learning, and classification-based ON/OFF control decision-making for air-conditioning systems. Rather than developing a new continuous control algorithm, this study investigates whether a classification-based decision layer can provide a practical approach for temperature regulation under real-world operational constraints.

Key contributions of this work are summarized as follows:

- An end-to-end AIoT framework integrating data acquisition, feature preparation, decision-making, and physical actuation in a closed-system greenhouse.
- A machine learning-based classification control formulation that converts continuous environmental sensing into discrete ON/OFF control decision-making for air-conditioning systems.
- Experimental validation in a real-world greenhouse environment to evaluate the practical feasibility of the proposed framework.

It should be noted that the proposed framework is developed and validated for temperature control in closed-system greenhouses cultivating cos lettuce under tropical climate conditions. The framework design, feature selection, and control formulation are therefore based on the specific growth characteristics and temperature requirements of this crop. While the framework itself is generic, applying it to other crops or cultivation environments would require appropriate adjustments in data collection, parameter configuration, and model training processes. Moreover, the selection of low-cost devices and cloud platforms was mainly intended to demonstrate the feasibility and practical implementation of the proposed concept. There are several alternative low-cost hardware solutions available, as well as free or low-cost

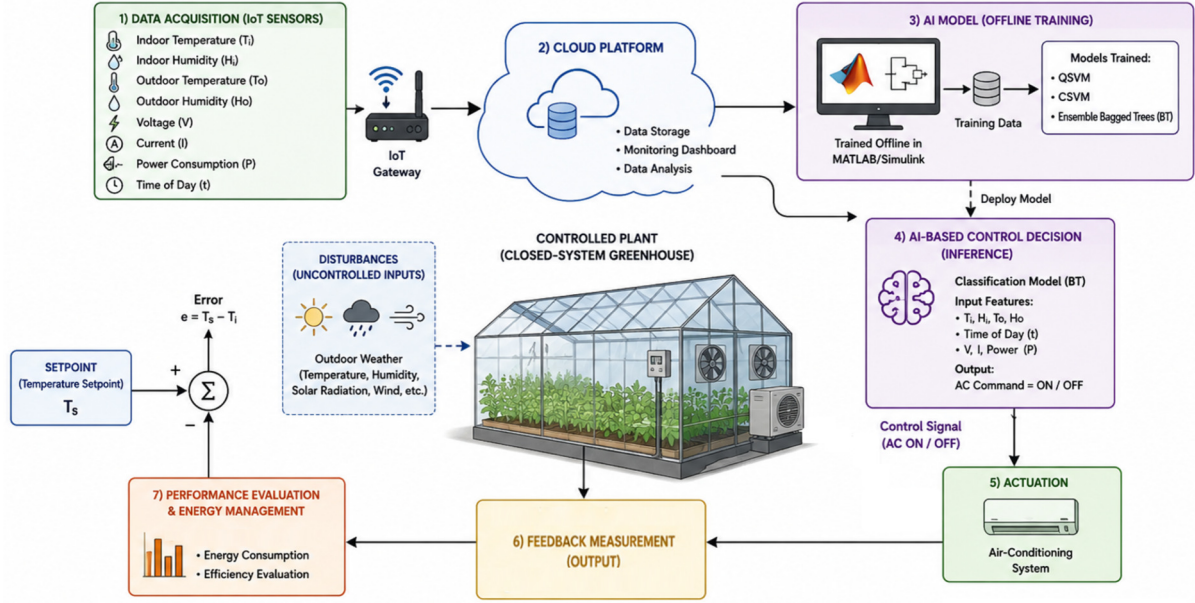


Fig.1: An AIoT framework for closed-system greenhouses.

cloud platforms that can be adopted depending on the application requirements.

The main findings of this study demonstrate the effectiveness of the proposed framework in practical greenhouse operation. The developed machine learning model achieved a classification accuracy of 98.46%, while the proposed control strategy achieved a 20.54% reduction in energy consumption compared with the conventional control approach. These results highlight the potential of the proposed AIoT framework for achieving accurate environmental control while improving energy efficiency in greenhouse applications.

The remainder of this paper is organized as follows. Section II presents the proposed AIoT framework for closed-system greenhouses. Section III describes the energy management approach via machine learning-based classification control. Section IV outlines the model development and evaluation procedures. Section V provides the real-world testing results and discussion, followed by concluding remarks.

2. AIOT FRAMEWORK FOR CLOSED-SYSTEM GREENHOUSES

This paper proposes an end-to-end AIoT framework integrating data acquisition, feature preparation, decision-making, and physical actuation in a closed-system greenhouse. As illustrated in Fig.1, the proposed framework consists of seven sequential steps as follows.

Step 1: Sensor-Based Data Acquisition

Environmental and electrical parameters are collected through IoT sensors deployed inside and outside the greenhouse. The acquired data include indoor temperature, indoor humidity, outdoor temper-

ature, outdoor humidity, voltage, current, power consumption, and time-of-day information. The collected sensor data are then transmitted through an IoT gateway for further processing and analysis.

Step 2: Cloud Data Management and Processing

The acquired sensor data are transferred to a cloud platform for data management and processing, including data storage, monitoring, and data analysis. The cloud platform serves as a centralized infrastructure for storing, organizing, and managing the collected information for subsequent AI model development and control decision-making.

Step 3: Offline AI Model Training

The collected dataset is utilized for offline machine learning model development in MATLAB/Simulink. The workflow includes data preparation, feature processing, model training, and performance evaluation. Multiple machine learning algorithms, including Quadratic Support Vector Machine (QSVM), Cubic Support Vector Machine (CSVM), and Ensemble Bagged Trees (BT), are trained and evaluated to identify the most suitable model. The best-performing model is then selected for deployment in real-world greenhouse control applications.

Step 4: AI-Based Control Decision (Inference)

The trained model is deployed as a real-time decision-making module for greenhouse operation control. The input features consist of indoor temperature, indoor humidity, time-of-day information, and electrical parameters including voltage, current, and power consumption. Based on these inputs, the model generates an air-conditioning ON/OFF control command. The classification model functions as a decision layer that determines appropriate control actions for regulating greenhouse environmental conditions.

Step 5: Physical Actuation

The control command generated by the AI model is transmitted to the IoT node, which serves as an interface between the AI-based decision layer and the physical actuation layer. The IoT node forwards the ON/OFF control signal to the control unit, where a magnetic contactor acts as the power switching interface for the air-conditioning load. This process regulates greenhouse environmental conditions based on real-time control decisions.

Step 6: Feedback Measurement

Following the execution of the control action, the greenhouse environmental conditions are continuously monitored to obtain feedback information for closed-loop operation. The monitored parameters mentioned in Step 1 are measured through the sensor network and fed back into the control system for subsequent decision-making and control cycles.

Step 7: Performance Evaluation and Energy Management

The overall system performance is evaluated using key performance indicators, including energy consumption and control performance metrics. These indicators are employed to assess the effectiveness of the proposed energy management framework in achieving energy-efficient greenhouse operation while maintaining the desired environmental conditions.

The control objective is defined by minimizing the temperature error:

$$e = T_s - T_i \quad (1)$$

where:

T_s denotes the temperature setpoint,

T_i denotes the measured indoor temperature, and e represents the temperature error.

The greenhouse environment is inherently affected by external disturbances, such as outdoor weather conditions, solar radiation, wind speed, and environmental temperature and humidity variations. However, these disturbance variables are not explicitly incorporated into the proposed control framework and will be considered in future work.

3. CLASSIFICATION-BASED ENERGY MANAGEMENT USING MACHINE LEARNING

In the proposed system, a machine learning-based classification control decision scheme is employed to determine an appropriate operating case for air-conditioning control. Instead of generating a continuous-valued control signal, the system classifies each operating condition into one of seven predefined control cases (Case 1- Case 7), as summarized in Table 1. Each case specifies a predefined ON/OFF operating schedule of the air-conditioning system within a 60-minute operating cycle. The objective of this approach is to achieve a balance between temperature

regulation performance and energy consumption.

Table 1: Air Conditioning Control Cases and the Corresponding On/Off Time Ratios.

Time(hr.)	On	Off
Case 1	Always On	
Case 2	50	10
Case 3	40	20
Case 4	30	30
Case 5	20	40
Case 6	10	50
Case 7	Always Off	

Although the greenhouse air-conditioning unit employs inverter technology, operational data indicate that compressor power decreases significantly as the indoor temperature approaches the target range. Therefore, this study assumes that temporary ON/OFF operation can further improve energy efficiency with minimal impact on temperature regulation. This assumption is adopted under a low-cost implementation constraint, where direct inverter-level control is not considered.

Accordingly, the control cases are defined based on the analysis of real operational data, considering indoor and outdoor environmental conditions and the energy consumption characteristics of the air-conditioning system. These predefined cases serve as target operating scenarios for classification-based ON/OFF control decisions from an energy management perspective.

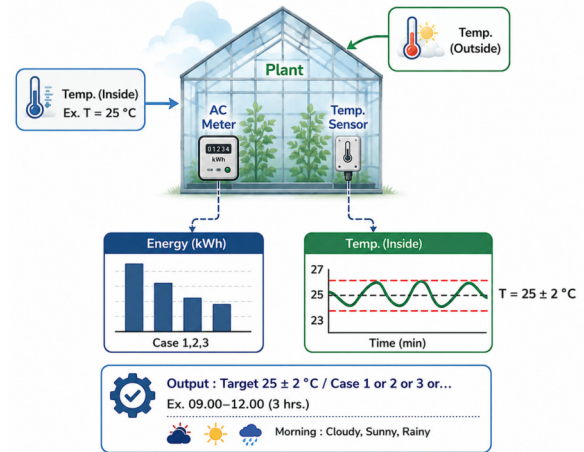


Fig.2: Classification-based on/off control scheme.

Fig. 2 illustrates the concept of greenhouse temperature control using the classification-based approach. The terms “Inside” and “Outside” shown in the figure correspond to indoor and outdoor environmental conditions, respectively. Based on a predefined temperature range (e.g., $25 \pm 2^\circ\text{C}$) and external weather conditions (such as cloudy, sunny, or rainy periods), the system selects the most appropriate control case (Case 1 - Case 7) for each time

interval. This allows the indoor temperature to be maintained within the target range while simultaneously evaluating energy consumption.

The classification model is trained using labelled data representing operating conditions maintained within a predefined temperature range while considering both plant growth requirements and energy efficiency. The dataset includes environmental variables such as indoor and outdoor temperature, relative humidity, and energy-related parameters. Following inference, the predicted class label corresponding to the selected control case is sent to the IoT node, which performs the associated ON/OFF control action.

4. REAL-WORLD IMPLEMENTATION

To validate the proposed concept, a prototype closed-system greenhouse was developed based on the AIIoT framework shown in Fig. 1 and the machine learning-based classification control approach. The implementation details are presented as follows.

4.1 Closed-System Greenhouse Configuration

A small-scale closed-system greenhouse was designed for controlled-environment cultivation. The greenhouse structure is constructed using transparent polycarbonate panels for both walls and roof, as shown in Fig. 3(a), allowing natural sunlight to pass through while enabling precise control of the internal environment. The greenhouse dimensions are 3.0 m $\times$ 2.4 m $\times$ 2.5 m (length $\times$ width $\times$ height).

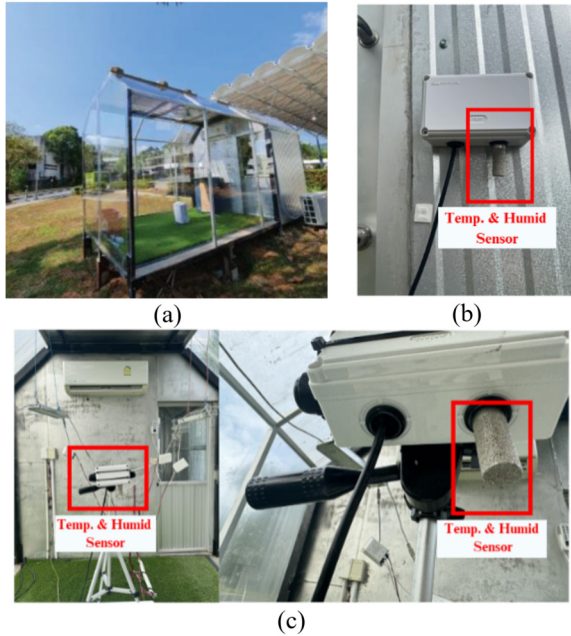


Fig.3: Physical greenhouse and sensor installation.

An air-conditioning system with a cooling capacity of 12,500 BTU/h (1,047 W) is installed inside the greenhouse to regulate the indoor temperature, which is a critical factor under hot and humid climatic

conditions. The target temperature is set to 25 $^{\circ}\text{C} \pm 2^{\circ}\text{C}$ for morning, afternoon, and nighttime periods. The cooling system operates under the machine learning-based classification control decision strategy described earlier, aiming to reduce unnecessary energy consumption by activating the air conditioner only when required to maintain suitable environmental conditions.

For environmental monitoring and data acquisition, two SHT45 temperature and relative humidity sensors are installed at key locations inside and outside the greenhouse, with one sensor located inside and the other outside, as illustrated in Fig. 3(b) and Fig. 3(c), respectively. In addition, electrical parameters of the air-conditioning system, including power, voltage, and current, are measured using a PZEM-004T energy sensor.

4.2 Data Collection and Experimental Scenarios

This study adopts a data-driven approach to develop a classification-based temperature control model for a closed-system greenhouse. The raw dataset was collected under multiple predefined air-conditioning control schemes, referred to as control cases, ranging from continuous operation (Case 1) to complete shutdown (Case 7), as summarized in Table 1. Each control case corresponds to a specific ON/OFF duty cycle applied during the experimental period.

The IoT-based data collection system used to acquire environmental and energy-related measurements from the greenhouse in real time. The objective of this section is to explain how sensor data are physically measured, transmitted, and stored prior to data preprocessing and analysis.

The IoT system consists of one IoT gateway node and three dedicated sensor nodes, all of which are implemented using ESP8266 microcontrollers.

- Sensor Node 1 measures outdoor temperature and relative humidity.
- Sensor Node 2 measures indoor temperature and relative humidity.
- Sensor Node 3 monitors the electrical energy consumption of the air-conditioning system using an AC power sensor.
- IoT Gateway node functions as a coordinator node, collecting data from the three sensor nodes and arranges the data into packets for transmission to the cloud.

The IoT system was tested in the laboratory prior to installation, with a measured power consumption of less than 3 W. Therefore, its power consumption was not included in the on-site measurements, as it was negligible compared with that of the air-conditioning system.

In addition, the latency for collecting data from the three sensor nodes and transmitting the aggregated

data to the cloud was measured during the laboratory test. The measured latency was less than 1 second. In this study, data transmission was performed every 5 minutes because temperature and relative humidity do not fluctuate rapidly under the considered operating conditions. Therefore, network latency is not a critical issue for the proposed system.

Moreover, during the experiment, internet connectivity interruptions were observed. The issue was analyzed and resolved by fixing the Wi-Fi channel of the dedicated router. Furthermore, a timestamp was added to each data packet, allowing the system to detect missing data and identify communication interruptions.

All sensor nodes transmit measurements at a fixed sampling interval of 5 minutes. This data collection enables synchronized acquisition of environmental and energy-related variables under real operating conditions. The collected measurements provide the raw sensor inputs used in the data preparation and model development processes described in subsequent sections.

The implemented system uses the ThingSpeak Free service, which supports up to 8 fields per channel with a minimum update interval of 15 seconds. The ESP8266 supports IEEE 802.11 b/g/n with a maximum theoretical PHY data rate of 72.2 Mbps. In our implementation, sensor data are transmitted every 5 minutes, and the transmitted sensor data are relatively small. Therefore, the communication bandwidth and ThingSpeak update-rate constraints do not adversely affect the operation of the proposed system under the current experimental conditions.

Data were collected from October 16, 2024, to May 31, 2025, covering a total duration of 228 days. To account for diurnal variations in environmental conditions, the dataset was divided into three time periods: morning (09:00–12:00), afternoon (13:00–16:00), and evening (18:00–00:00). This temporal segmentation allows the learning process to distinguish between control actions and natural environmental changes that occur at different times of the day.

For model training and evaluation, data selection was performed based on both temperature regulation performance and energy efficiency. Only data segments in which the applied control case was able to maintain the indoor greenhouse temperature within the target range of 23–27 °C, while exhibiting reasonable and non-excessive air-conditioning energy consumption (E, kWh), were retained. If a control case on a given day failed to satisfy either temperature or energy criteria, the corresponding data segment was excluded from the training dataset. This filtering strategy was applied to prevent the model from learning inappropriate or misleading control patterns.

In addition, each experimental segment was limited to approximately three hours to reduce the influence of thermal accumulation caused by prolonged

air-conditioning operation. Continuous cooling can prevent the greenhouse from returning to comparable initial thermal conditions between experiments. Introducing time gaps between operating periods allows accumulated heat within the greenhouse structure to dissipate, resulting in more consistent initial conditions across data samples.

The resulting dataset represents a curated collection of environmental and energy-related measurements that reflect realistic greenhouse operating conditions. These raw data serve as the basis for subsequent feature selection, model development, and performance evaluation.

4.3 Model Development

According to the proposed framework and system design, this section presents the development of machine learning models for classification-based air-conditioning control in the greenhouse environment. The objective is to develop a reliable control decision model capable of supporting ON/OFF air-conditioning operation while maintaining appropriate indoor conditions and reducing unnecessary energy consumption.

Three supervised learning classification models were developed using the MATLAB Classification Learner App (MATLAB 2023a): Quadratic Support Vector Machine (QSVM), Cubic Support Vector Machine (CSVM), and Ensemble Bagged Trees (BT). The selected dataset was randomly divided into training (80%) and testing (20%) subsets. The training data were used for model learning and performance evaluation through five-fold cross-validation, while the testing data were reserved for final model assessment.

Initially, 15 input features were considered, including environmental parameters, electrical measurements, temperature control indicators, and time-related variables, as listed in Table 2. To reduce model complexity and identify the most informative variables, feature importance ranking was performed using the Minimum Redundancy Maximum Relevance (mRMR) method. This approach evaluates the relevance of each variable to the target control class while minimizing redundancy among selected features.

Based on the obtained mRMR rankings, a manual feature elimination process was conducted by progressively removing the least important variables and retraining the models to evaluate the impact of feature reduction on classification performance. The resulting feature subsets were then used to assess the generalization capability, classification stability, and misclassification behavior of each model under practical operating conditions.

The overall results are used to determine the most suitable model for real-world implementation, considering not only predictive accuracy but also model

Table 2: Description of Input Features and Associated Definitions.

Feature	Equation/Meaning
Hours	time in 24-hour format
time.period	time segment (morning: 1, afternoon: 2, evening: 3)
LowerTemp	lower bound of the target temperature range (2 °C from setpoint)
TempSet	target temperature setpoint (25 °C)
UpperTemp	upper bound of the target temperature range (+2 °C from setpoint)
OTemp, OH	outdoor temperature and outdoor humidity
ITemp, IH	indoor greenhouse temperature, and indoor relative humidity respectively.
Voltage, Current, Power	electrical parameters of the cooling system
deltaToutside	$\Delta T_{outside} = T_{outside}(t) - T_{outside}(t-1)$
deltaTinside	$\Delta T_{inside} = T_{inside}(t) - T_{inside}(t-1)$
deltaTinout	$\Delta T_{out-in} = T_{outside}(t) - T_{inside}(t)$

simplicity, robustness, and consistency with the proposed control framework.

4.4 Machine Learning-Based Classification Control Decision using MATLAB Simulink

After developing and selecting the appropriate machine learning classification models, this section presents the development of the machine learning-based classification control decision process using MATLAB Simulink. This development represents a core component of the proposed intelligent control system, where classification results are translated into ON/OFF control commands for the greenhouse cooling system based on environmental sensor data.

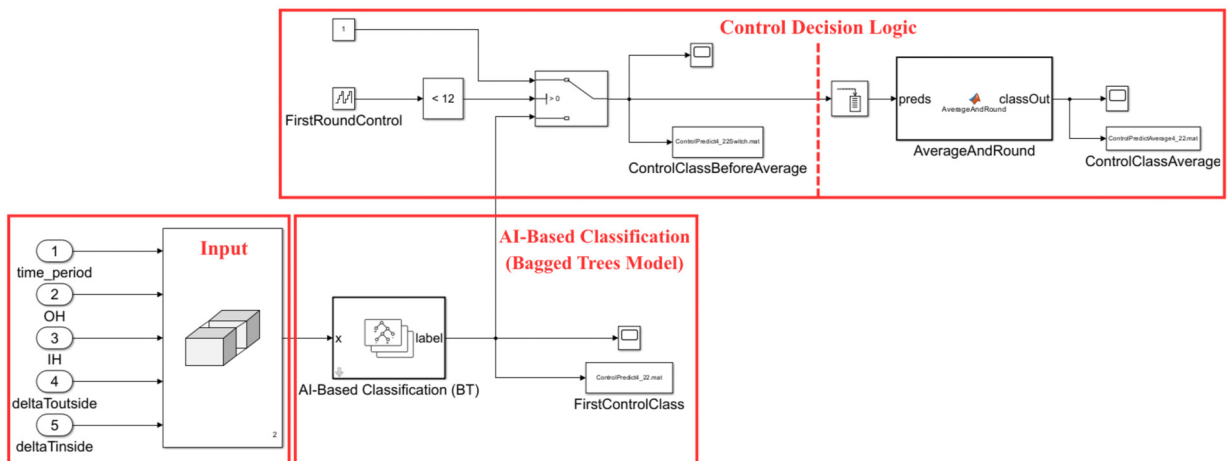
In the proposed framework, the final system is designed for real-world deployment through cloud-based platforms such as ThingSpeak, which provides direct integration with MATLAB for data acquisition and control implementation. However, at the current stage, MATLAB Simulink is employed in an offline operation environment to implement and validate the control decision process. This approach allows the performance and stability of the decision logic to be evaluated clearly before real deployment.

The implemented Simulink model in Fig. 4 consists of three main components: (1) input data processing, (2) AI-based classification, and (3) control decision logic. The Simulink model receives sensor-based input variables, including temperature, humidity, time information, and electrical energy parameters. These inputs are fed into the trained machine learning-based classification model embedded within a Simulink block. The model outputs a predicted control class, which represents one of the predefined ON/OFF control cases for the air-conditioning system. This output is then processed by the control decision logic to generate the final control command.

Due to platform constraints of ThingSpeak, which allows a maximum of eight data fields per channel, only classification models using no more than eight input features are considered in this model. This limitation ensures that the developed models can be directly deployed in the actual cloud-based system without modification. Based on this concept, a cloud-oriented processing model was constructed in Simulink.

The AI-based classification module, represents the trained classification model imported from MATLAB. The input feature vector is fed into the model through the input port, and the output is provided as a predicted class label. This label corresponds to one of the seven predefined air-conditioning control cases described in Table 1. The predicted result is stored as the variable FirstControlClass, which represents the raw classification output before further decision refinement.

The control decision logic is divided into two main stages: the initial control decision and the averaged control decision. During the initial stage, the system applies a fixed control strategy (Case 1: always ON) to ensure that the greenhouse temperature quickly reaches the desired range at the start of operation. This initial phase covers the first 12 control intervals, where each interval corresponds to 5 minutes, result-


Fig.4: AI-based control framework for greenhouse air-conditioning implemented in Simulink.

ing in a total duration of one hour.

After sufficient prediction data have been accumulated, the system switches to the averaged control decision stage. In this stage, the most recent 12 predicted control classes are retrieved from memory and averaged using the AverageAndRound function. The final control command is selected as the predefined class that is closest to the averaged value. This averaging process smooths short-term fluctuations in model predictions and prevents frequent switching of the air-conditioning system. As a result, system stability is improved, compressor wear is reduced, and unnecessary energy consumption caused by frequent ON/OFF cycles is minimized. The final control command is stored as ControlClassAverage and used as the control input for the next operating period.

To improve system robustness in practical deployment, a local fail-safe control mechanism can be incorporated at the gateway or edge level. In the event of network disconnection or excessive communication latency, predefined temperature thresholds or the last valid control state can be used to maintain basic air-conditioning control locally. This mechanism would provide continuous operation during temporary cloud or network failures and will be considered in future implementation.

5. EVALUATION RESULTS

This section presents the data analysis results and the performance evaluation of the classification models developed for air-conditioning control in the greenhouse. The objective of this analysis is to assess the suitability of the proposed models for supporting ON/OFF control decisions under practical operating constraints, with emphasis on maintaining indoor temperature within an appropriate range while avoiding unnecessary energy consumption.

The analysis begins with an evaluation of input feature importance using the mRMR method. This step aims to identify a subset of input variables that are highly relevant to control decision-making while minimizing redundancy among features. Feature selection is an essential component of the proposed framework, as it helps reduce model complexity and improves robustness for real-world deployment.

Subsequently, this section presents the development and evaluation of air-conditioning control classification models based on three machine learning algorithms: QSVM, CSVM, and BT. The evaluation focuses on model generalization behavior, the balance between training and testing performance, and the patterns of misclassification among control cases with similar operating characteristics. These aspects are particularly important for ensuring reliable and stable control decisions in practical greenhouse applications.

Finally, the results presented in this section are used to support the selection of an appropriate model

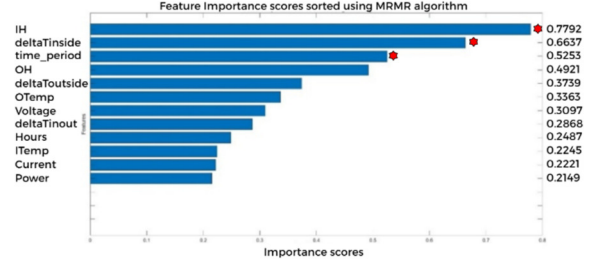


Fig.5: Feature importance ranking based on the mRMR algorithm.

for real-world implementation in a smart greenhouse control system. Model selection is based on stability, simplicity, and consistency with the proposed control process framework, rather than on achieving the highest predictive accuracy alone.

5.1 Feature Selection Results

To identify the most informative and non-redundant input variables for classification-based air-conditioning control, feature selection was performed using the mRMR method. This technique evaluates each input variable based on its statistical relevance to the target control class while simultaneously minimizing redundancy among selected features. The use of mRMR is particularly suitable for data-driven control applications, as it helps reduce model complexity and improve generalization performance under real-world operating conditions.

Fig. 5 presents the feature importance ranking obtained from the MATLAB Classification Learner App based on mRMR scores. The results indicate that indoor humidity (IH) is the most influential variable, with an mRMR score of 0.7792, followed by the indoor temperature deviation from the target setpoint (deltaTinside, 0.6637), time period (0.5253), and outdoor humidity (OH, 0.4921). These variables are directly related to the thermal and moisture dynamics inside the greenhouse and therefore play a critical role in determining appropriate ON/OFF operating decisions for the air-conditioning system.

Other variables, including outdoor temperature (OTemp), temperature difference between indoor and outdoor environments (deltaToutside), electrical measurements such as voltage, current, and power, and time-related variables (Hours), exhibited lower but still meaningful importance scores. Although these features contribute less individually, they provide complementary information regarding environmental conditions and system operating states. Based on the mRMR ranking, subsequent model development focused on selecting compact feature subsets that balance predictive relevance and practical deployment constraints, particularly the limitation on the number of input fields supported by the cloud platform.

Based on the feature importance ranking obtained from the mRMR analysis, the next step is to examine how different subsets of selected features affect the performance and stability of machine learning-based classification control models. Rather than maximizing predictive accuracy through the inclusion of all available variables, the objective is to identify a feature set that provides reliable control decisions while maintaining low model complexity and suitability for real-world greenhouse deployment.

5.2 Model Evaluation Results

According to the feature selection, three supervised machine learning-based classification models were developed and evaluated for air-conditioning control decision-making: QSVM, CSVM, and BT. These models were selected to represent different levels of model complexity and computational characteristics, allowing a fair comparison from a system design perspective rather than an algorithmic competition.

To assess the impact of feature selection on model behavior, features were gradually eliminated according to their mRMR ranking, and the models were re-trained and evaluated at each step. Fig. 6 illustrates the variation in classification accuracy for both training and testing datasets as a function of the number of input features. Fig. 6(a) shows the variation in training accuracy as the number of selected features increases, while Fig. 6(b) presents the corresponding performance on the testing dataset. This separation allows the generalization behavior of each model to be examined explicitly, rather than relying solely on overall accuracy values.

As shown in Fig. 6(a), all three models exhibit increasing training accuracy as more features are included, with performance saturating when approximately 8–10 features are used. However, Fig. 6(b) indicates that beyond this range, additional features do not consistently improve testing performance and may even degrade generalization, particularly for the Bagged Trees model.

This observation indicates that a moderate number of informative features is sufficient to capture the key patterns required for reliable control decision-making. Introducing additional features beyond this point increases model sensitivity to redundancy and noise, leading to reduced generalization performance rather than further accuracy gains.

Among the evaluated models, QSVM using 10 input features achieved the highest test accuracy of 98.46% while maintaining a good balance between training (97.74%) and testing performance. This balance suggests stable generalization behavior and indicates that the selected feature subset captures the key factors required for reliable control decision-making. In comparison, CSVM required 11 features to reach its optimal performance, with a slightly lower test accuracy of 96.92%. Given the higher model com-

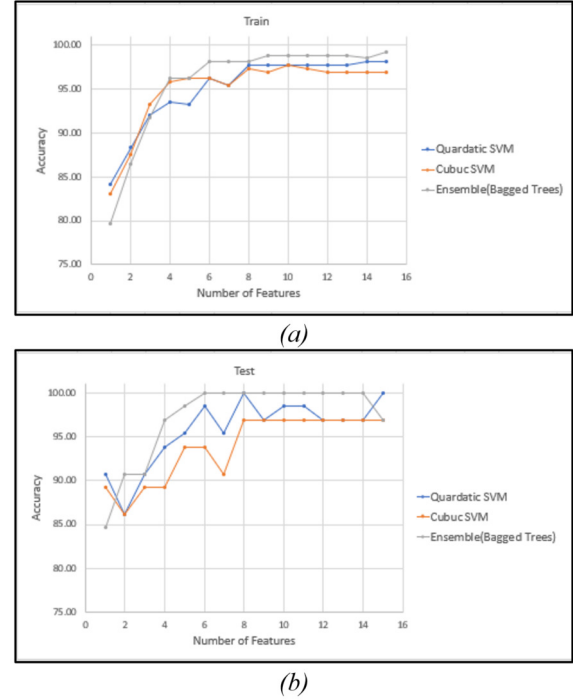


Fig. 6: Effect of Feature Subset Size on Training and Testing Accuracy of Classification-Based Air-Conditioning Control Models (QSVM, CSVM, And Bagged Trees).

plexity and marginal performance difference, CSVM was not considered further, as it does not provide a clear advantage for practical implementation.

The Bagged Trees model achieved comparable test accuracy (98.46%) using only 5 features, demonstrating its ability to perform well with a compact input set. However, its training accuracy (96.23%) was lower than that of QSVM, and its performance showed greater sensitivity to feature selection. While BT offers advantages in terms of low computational complexity and reduced inference time—making it attractive for resource-constrained systems—the QSVM model provides a more consistent balance between stability and performance within the proposed machine learning-based classification control framework designed for practical greenhouse deployment. Nevertheless, given the ThingSpeak platform constraint of eight data fields per channel and the requirement for a deployable low-cost system, the BT model—which achieves equivalent accuracy using only 5 features—is selected for real-world implementation in this study.

The training dataset was intentionally filtered to include only segments in which the indoor temperature remained within the target range (23–27 °C) and energy consumption was considered acceptable. This design choice prevents the model from learning undesirable control behavior. However, it also reduces exposure to extreme or highly variable seasonal conditions. Consequently, the reported classification ro-

bustness should be interpreted within the context of the collected operating range.

5.3 Confusion Matrix Analysis and Class-Level Evaluation

In this study, confusion matrix analysis is conducted to examine the class-level classification behavior of the developed models. Here, the term “Class” is used to represent the predefined air-conditioning control cases, which are equivalent to the control “Cases” defined earlier in this work. Each class corresponds to a specific ON/OFF duty cycle of the air-conditioning system.

Fig. 7, Fig. 8, and Fig. 9 present the confusion matrices obtained from the MATLAB Classification Learner App for the QSVM, CSVM, and BT models, respectively. These results provide insight into misclassification patterns that are not fully captured by overall accuracy metrics.

As shown in Fig. 7, the QSVM model correctly classified Class 1, Class 5, and Class 7 with 100% accuracy. These classes represent extreme control strategies, including Always OFF and Always ON operation modes. This result indicates that the QSVM model is highly reliable in distinguishing critical boundary conditions of the control space.

However, for Class 3, the true positive rate (TPR) decreases to 80.6%, with 19.4% of samples misclassified as Class 5. This misclassification reflects the similarity between the ON/OFF duty cycles of these two cases—Class 3 (40 minutes ON / 20 minutes OFF) and Class 5 (20 minutes ON / 40 minutes OFF)—rather than a failure of the model to recognize fundamentally different control behaviors.

Fig. 8 presents the confusion matrix of the CSVM model. Compared to QSVM, CSVM exhibits a lower TPR for Class 3 (77.4%), with a corresponding false negative rate (FNR) of 22.6%. Despite this reduction, no severe misclassifications were observed, such as switching between Always ON and Always OFF cases. This behavior. Although CSVM shows reduced discrimination for intermediate duty-cycle cases, it does not produce contradictory extreme decisions.

In contrast, Fig. 9 illustrates the confusion matrix of the BT model, where bidirectional misclassification between Class 3 and Class 5 is observed. Specifically, Class 3 is misclassified as Class 5 in 19.4% of cases, while Class 5 is misclassified as Class 3 in 13.8% of cases. Although this mutual confusion indicates reduced precision in distinguishing similar duty cycles, both classes correspond to active cooling operation. As a result, these errors are not expected to cause severe control failures, but may introduce small deviations in ON/OFF timing.

Overall, confusion matrix analysis reveals that all tested models experience some degree of misclassification between Class 3 and Class 5, which have closely

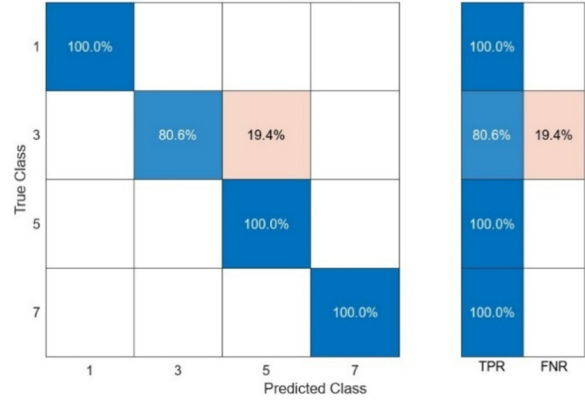


Fig.7: Confusion Matrix of QSVM.

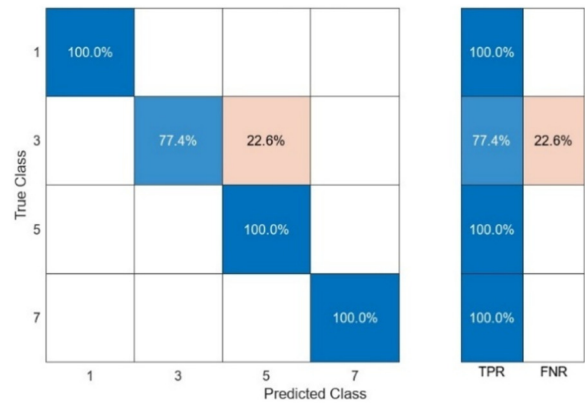


Fig.8: Confusion Matrix of CSVM.

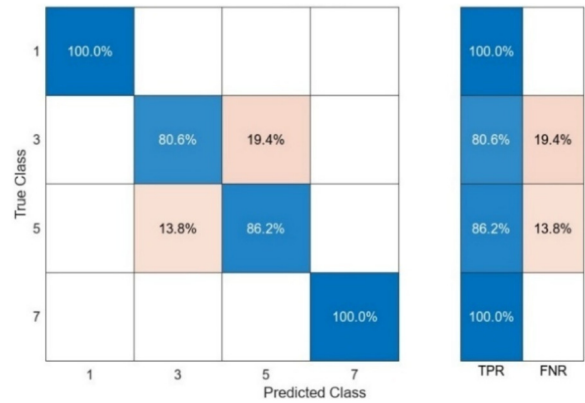


Fig.9: Confusion Matrix of BT.

related control patterns. Importantly, these errors do not result in unsafe or contradictory control actions, as both classes maintain cooling operation. Nevertheless, reducing misclassification among similar duty-cycle cases would improve control granularity and energy efficiency.

It should also be noted that the dataset used for training was filtered to include only periods in which the indoor temperature remained within the target range of 23–27 °C and energy consumption was considered reasonable. While this filtering helps prevent the model from learning inappropriate control behav-

ior, it also reduces data diversity, particularly across different seasonal conditions. Limited data availability may therefore restrict the model's ability to fully capture subtle control distinctions under more diverse environmental scenarios. Future studies incorporating longer-term and multi-season datasets could further enhance classification robustness and generalization performance.

6. VALIDATION IN A REAL GREENHOUSE

Following the offline analysis and model evaluation presented in Section 5, this section focuses on validating the proposed machine learning-based classification control framework under real greenhouse operating conditions. The objective is to assess whether the selected control formulation can be practically deployed to support air-conditioning ON/OFF decisions while maintaining indoor temperature within the desired range and reducing unnecessary energy consumption.

The evaluation is conducted using real sensor data and an implemented control system, allowing both system-level behavior and energy usage to be observed. This section first introduces the control system architecture and experimental setup, followed by an analysis of real-time power and energy profiles, a comparison with baseline operation, and representative case studies illustrating control decisions under varying environmental conditions.

6.1 Experimental Setup and Control Framework

The experimental validation was conducted in a closed-system greenhouse under real operating conditions. The control framework integrates real-time sensor data acquisition, machine learning-based classification, and a rule-based control decision logic implemented in MATLAB/Simulink.

The input variables provided to the classifier include time period, indoor humidity (IH), outdoor humidity (OH), indoor temperature difference (ΔT_{inside}), and outdoor temperature difference ($\Delta T_{\text{outside}}$), as identified through the feature selection process described in Section 4. Based on these inputs, a BT classification model predicts one of seven predefined control classes, each corresponding to a specific air-conditioning ON/OFF duty cycle.

The predicted control class is subsequently processed by the control decision logic before being issued as an actuation command to the air-conditioning system. For performance comparison, the system was evaluated under two scenarios: (1) control using the proposed AI-based framework and (2) baseline operation without machine learning, in which the air-conditioning system remained continuously ON.

6.2 Real-Time Control Results Using the Proposed Framework

The proposed control framework was experimentally evaluated over two comparable test days under similar operating conditions to reduce potential bias caused by short-term weather variability. The objective was to examine whether the classification-based ON/OFF control strategy demonstrates consistent behavior across multiple real-world scenarios.

According to the overall control framework implemented in Simulink, the AI-based classification module based on BT model is employed to determine appropriate ON/OFF control cases, while a control decision logic processes the classification outputs before issuing final commands to the air-conditioning system. Fig. 10 illustrates the control workflow results in the real-world testing phase. The upper panel presents the output of the AI-based classification module using the BT model, which predicts control cases based on the input conditions. Due to variations in consecutive predictions, the classification output exhibits frequent transitions among different control cases. The middle panel shows the initial control decision generated directly from the classification results, where rapid fluctuations are still observed. To improve control stability, an averaging mechanism is applied, as shown in the lower panel. The averaged control decision smooths short-term fluctuations and suppresses abrupt switching behavior, resulting in more stable control actions and reducing excessive ON/OFF operations of the air-conditioning system.

Fig. 11 and Fig. 12 illustrate the power profile and cumulative energy consumption for one representative test day under BT-based control. This day is presented for clarity of visualization, while similar control patterns were observed on the second test day, confirming the consistency of system behavior.

Fig. 11 shows the power profile of the greenhouse air-conditioning system. The dynamic ON/OFF cycling behavior reflects the machine learning-based classification control decisions generated by the proposed framework. Instead of continuous operation, the system adapts its duty cycle according to environmental conditions.

Fig. 12 presents the corresponding cumulative energy consumption. The stepwise increase in energy reflects intermittent cooling operation. Periods of reduced cooling activity occur when indoor temperature remains within the acceptable range (23–27 °C), indicating that the framework avoids unnecessary energy usage while maintaining suitable thermal conditions for crop growth.

The similar behavior observed across both test days suggests that the proposed framework provides stable and repeatable control performance under comparable environmental conditions

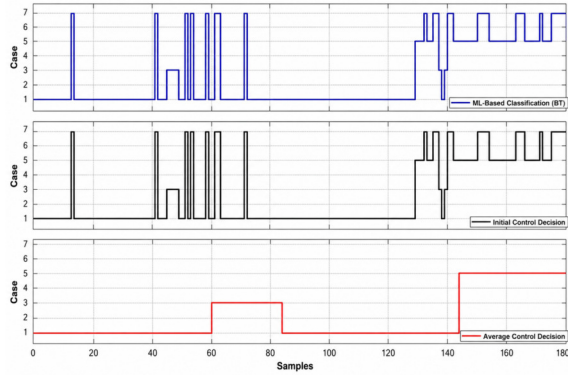


Fig.10: Control decision process in Simulink: AI-based classification (top), initial control decision (middle), and averaged control output (bottom).

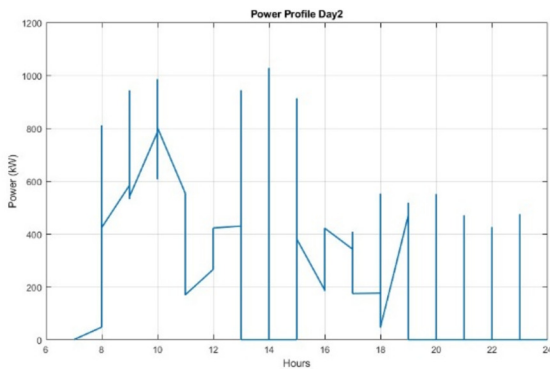


Fig.11: Power Consumption Profile On Test Day 1 Under BT-Based Control.

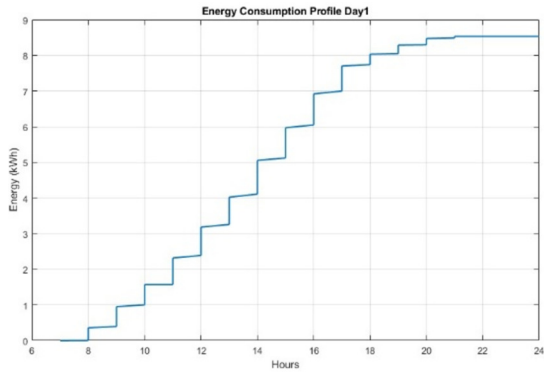


Fig.12: Cumulative energy consumption on Test Day 1 under BT-based control.

6.3 Control Behavior Analysis

To further investigate the control behavior, this section presents a representative case study that illustrates how outdoor temperature, indoor temperature, and the control decisions generated by the BT model interact over time.

During periods of high outdoor temperature, the model selected moderate-duty control cases (e.g., Case 3), corresponding to longer cooling durations. As outdoor conditions gradually improved, the con-

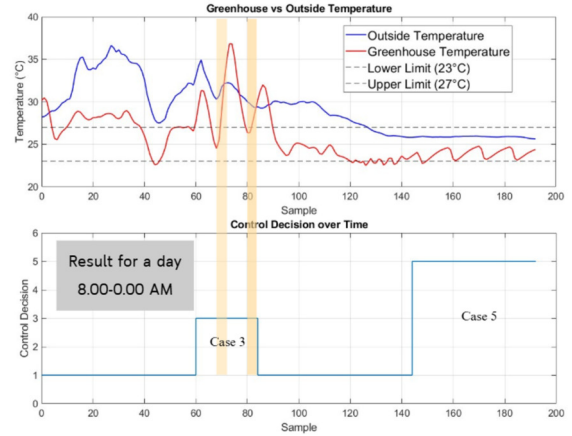


Fig.13: Example of Real-Time Operation of The BT Model Showing The Relationship Between Greenhouse Temperature, Outdoor Temperature, And Selected Control Cases.

trol decision transitioned to lower-duty cases (e.g., Case 5), reducing cooling time while maintaining the indoor temperature within the desired range.

This behaviour highlights the interpretability of the machine learning-based classification control formulation, where control decisions can be directly mapped to predefined operational cases. Although occasional transitions between similar cases were observed, these transitions did not result in unsafe control actions, as all selected cases remained within active cooling modes.

Fig. 13 illustrates the real-time operational behaviour of the BT-based classification model by presenting indoor temperature, outdoor temperature, and the corresponding discrete control decisions over time. The upper and lower temperature limits (27 °C and 23 °C) define the acceptable thermal range for crop cultivation. During the early period of operation, the indoor temperature remains within the acceptable range, and the controller maintains a low-level decision state (Case 1), indicating minimal cooling activity. Around sample 60–80, when indoor temperature approaches or slightly exceeds the upper limit, the model transitions to Case 3, representing an intermediate cooling response. In the later stage (after approximately sample 145), the model activates Case 5, corresponding to a stronger cooling decision as temperature conditions require more intensive regulation. This stepwise transition among discrete control cases demonstrates how continuous environmental measurements are translated into classification-based ON/OFF decision levels, enabling adaptive yet computationally simple control suitable for low-cost greenhouse systems.

6.4 Energy Consumption Comparison

Fig. 14 compares the total energy consumption between the proposed AI-based control and the base-

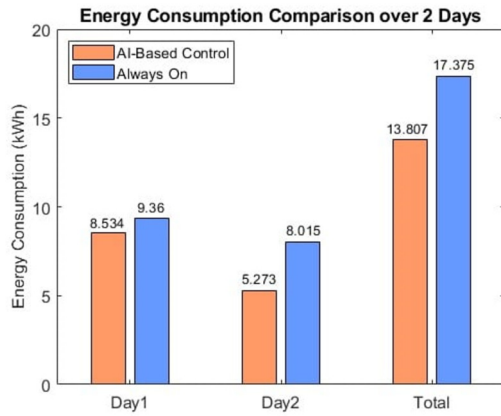


Fig.14: Comparison Of Total Energy Consumption Between The Model-Based Control (BT) and The Baseline Control Without A Model.

line control strategy over the same test period. The results indicate that the system operating with the BT-based control consumed 13.807 kWh, while the baseline system consumed 17.375 kWh, corresponding to an energy reduction of approximately 20.54%.

This result demonstrates the potential of the proposed framework to reduce energy consumption under real greenhouse operating conditions. However, the reported reduction should be interpreted as an initial validation rather than a definitive performance guarantee.

6.5 Discussion and Practical Implications

The experimental results confirm that the proposed framework can be deployed in a real greenhouse environment and can effectively support ON/OFF air-conditioning control decisions under practical constraints. Rather than optimizing a continuous control signal, the framework emphasizes decision reliability, system simplicity, and interpretability, which are critical for low-cost greenhouse applications.

It should be noted that the experimental evaluation was conducted over a limited number of test days. While efforts were made to select comparable days to reduce weather-related bias, the results may not fully capture seasonal variability or extreme environmental conditions. Consequently, the reported energy reduction should be viewed as an initial indication of feasibility rather than a universal performance metric.

Future work will focus on extending the evaluation period across different seasons and refining the control case definitions to further improve robustness under highly variable climatic conditions.

7. CONCLUSION

This study has proposed a classification-based air-conditioning control framework for closed-system greenhouses operating under hot and humid climate

conditions. The control strategy formulates air-conditioning operation as a discrete decision problem, where predefined ON/OFF control cases are classified using supervised machine learning models, including Quadratic Support Vector Machine (QSVM), Cubic Support Vector Machine (CSVM), and Ensemble Bagged Trees (BT).

Seven candidate control cases were initially defined based on different ON/OFF duty cycles. From these, a subset of feasible control patterns was selected to support energy-efficient operation, stable temperature regulation, and reduced mechanical stress on cooling equipment caused by frequent switching. The proposed framework enables the controller to select an appropriate control case rather than directly computing continuous control signals, thereby simplifying the control logic while maintaining operational flexibility.

Experimental results demonstrate that QSVM and BT achieved the highest classification performance, with a maximum test accuracy of 98.46% and low RMSE values. These results indicate that the proposed framework is capable of supporting reliable control decisions that balance energy efficiency and thermal comfort in practical greenhouse operation.

Key findings of this study can be summarized as follows:

- Case-based classification simplifies control decision logic while preserving adaptability to changing environmental conditions.
- Feature selection using mRMR improves model reliability by identifying informative and non-redundant variables, with indoor humidity, time-related variables, and temperature differences consistently emerging as dominant features.
- Different control cases exhibit varying effectiveness across time periods, suggesting that discrete, time-aware control patterns can better reflect real greenhouse operating conditions than static control rules.

Overall, the results confirm that the proposed machine learning-based classification control framework provides a practical and interpretable alternative to continuous or optimization-based control methods, particularly for low-cost and deployable greenhouse systems.

Finally, future research should focus on real-time embedded implementation with closed-loop feedback and the integration of geospatial weather and climate data to enable predictive temperature control. Multi-season and multi-location data collection will further enhance the scalability of the proposed framework for Smart Agriculture.

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AUTHOR CONTRIBUTIONS

Conceptualization, N. Jindapetch and M. Dangsalae; methodology, N. Jindapetch and M. Dangsalae; software, A. Traisuwan and M. Dangsalae; validation, A. Traisuwan, M. Dangsalae and N. Jindapetch; formal analysis, A. Traisuwan; investigation, M. Dangsalae; data curation, M. Dangsalae; writing—original draft preparation, M. Dangsalae and N. Jindapetch; writing—review and editing, A. Booranawong, K. Sengchuai and D. Buranapanichkit; visualization, M. Dangsalae and A. Traisuwan.; supervision, N. Jindapetch; funding acquisition, N. Jindapetch All authors have read and agreed to the published version of the manuscript.

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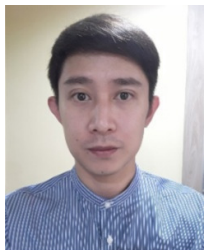
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