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VARFIS: A Hybrid Neuro-Fuzzy Model for Intelligent Microclimate Control in Black Soldier Fly Farming Systems

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ABSTRACT

Maintaining optimal microclimate conditions is essential for Black Soldier Fly (BSF) cultivation, yet traditional systems often struggle with dynamic environmental changes. This study proposes the Vector Autoregressive-Fuzzy Inference System (VARFIS), a hybrid model combining Vector Autoregression (VAR) and Adaptive Neuro-Fuzzy Inference System (ANFIS), to enhance temperature and humidity control in BSF insectariums. VARFIS adapts to uncertainty using probabilistic learning, achieving a 48% reduction in prediction error (MAPE = 1.36%) and high accuracy (R^2 = 0.9695), outperforming standalone VAR and ANFIS models. The model effectively captures daily climate fluctuations, improving larval growth efficiency and waste conversion. However, it remains limited in handling extreme events such as sudden heatwaves or humidity spikes, indicating the need for enhancements like adaptive fuzzy rule tuning and integration of physical constraints. VARFIS presents a scalable solution for intelligent microclimate management, supporting sustainable insect farming and circular economy goals. This work contributes to precision agriculture by offering data-driven tools for resilient environmental control.

Keywords : *BSF; microclimate control; VARFIS; precision agriculture; sustainable insect farming.*

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1. INTRODUCTION

Maintaining optimal environmental conditions is critical in the cultivation of Black Soldier Fly (BSF), especially in enclosed insectarium systems. Temperature and humidity significantly affect larval development, waste conversion efficiency, and survival rates. When these abiotic factors fluctuate outside the optimal range of 26–30°C and 60–90% humidity, larvae experience slowed growth and increased mortality. Current systems often lack the intelligence and adaptability needed to regulate these variables consistently. This creates an urgent need for a reliable and responsive control mechanism that can ensure microclimate stability.

To address this, intelligent modeling approaches such as the Vector Autoregressive-Fuzzy Inference System (VARFIS) offer promising solutions. VARFIS combines the adaptability of neural networks with the transparency of fuzzy logic, allowing it to learn and infer complex environmental patterns. Unlike traditional control methods, VARFIS can adapt in real time and handle uncertainty in environmental data. Its potential application in BSF cultivation could significantly improve larval health and productivity by maintaining ideal microclimate conditions. Therefore, integrating VARFIS into BSF systems represents a crucial step toward sustainable and efficient insect farming.

BSF farming systems require careful control of temperature and humidity for optimal growth and development. Research indicates that temperatures between 26-30°C and relative humidity of 60-90% are ideal conditions for BSF rearing [1]. Maintaining appropriate substrate moisture is crucial, with excessive moisture leading to low biomass and high mortality [2]. To address this, dry materials like rice husk and rice bran can be added to substrates, though their proportions must be carefully managed [2]. Internet of Things (IoT) technology has been proposed to monitor and control these parameters remotely, potentially improving efficiency in BSF farming [3]. However, limitations in current systems include challenges in maintaining consistent conditions, the need for substrate pretreatment, and the impact of abiotic factors on larval development and composition [1], [4].

Intelligent systems play crucial roles in environmental control for agriculture and insect farming. Fuzzy logic-based systems have been developed to optimize irrigation timing and water usage in cotton farming, while also addressing pest issues like whitefly infestations [5]. Similar fuzzy logic controllers integrated with IoT devices have been applied to general agricultural systems, managing factors such as soil moisture, temperature, and humidity [6]. In mushroom cultivation, IoT and fuzzy logic integration has improved substrate environment management, including watering, light control, and pest detection [7]. For greenhouse environments, intelligent fuzzy auxiliary cognitive systems (IFACS) have demonstrated effectiveness in adaptive control and supply chain management, maintaining optimal temperature ranges and reducing greenhouse gas emissions [8]. These applications showcase the potential of intelligent systems in enhancing agricultural productivity and sustainability through precise environmental control.

Recent studies have demonstrated the effectiveness of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) in regulating environmental parameters relevant to smart farming and insect rearing. In precision agriculture, ANFIS has been applied to control greenhouse temperature and humidity, showing high accuracy and adaptability to fluctuating conditions [9]. In BSF farming environments, maintaining stable microclimate conditions, particularly temperature and humidity is critical for optimal larval development. ANFIS has been utilized in environmental control systems to model such nonlinear dependencies, often outperforming classical statistical models in prediction accuracy [10]. The integration of ANFIS with optimization algorithms like Genetic Algorithm (GA) has been shown to enhance performance by automatically tuning membership functions and rule sets [11]. However, effective deployment still requires adequate training data and careful model configuration. These studies highlight the relevance of ANFIS-based models in supporting dynamic microclimate management for sustainable BSF cultivation.

To strengthen the contextual foundation of this study, we have expanded the literature review to include recent and relevant models in environmental prediction. Deep learning approaches like LSTM [12], CNN-GRU

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hybrids [13], and Kalman Filter-based methods [14] have shown strong performance in forecasting temperature and humidity under uncertain and dynamic conditions. Compared to these, our proposed VARFIS model integrates statistical and fuzzy reasoning to provide both interpretability and adaptability. This addition positions our work more clearly within current research trends in precision agriculture.

Uncertainty in environmental data significantly impacts control systems performance, prompting research into variational methods as a solution. [13] found that organizational control interactions become less complementary and more substitutive as environmental uncertainty increases. [14] proposed an end-to-end neural scheme using variational Bayes inference to address data assimilation and uncertainty quantification in geosciences. [15] developed a framework for simulating home energy management systems under uncertain conditions, demonstrating that stochastic model predictive control outperforms deterministic and heuristic methods. [16] showed that incorporating environmental factors like wind shear and turbulence intensity into Gaussian process models improves the accuracy and reduces uncertainty in wind turbine power curve modeling. These studies highlight the importance of accounting for environmental uncertainty in control systems and the potential of variational methods to address this challenge.

BSF larvae are effective in organic waste management and protein production, with their performance influenced by various factors. Substrate composition significantly affects larval growth, waste reduction efficiency, and bioconversion rates [17]. Optimal larval density, feed dose, and substrate depth are crucial for maximizing bioconversion efficiency and material reduction [18]. While the presence of (micro)plastics in substrates does not significantly impact larval growth or survival [19], larval activity generates substantial heat, affecting production parameters. Population density, size, and air temperature play important roles in larval development and feed conversion ratios [20]. Shifting larvae from higher to lower temperatures during rearing can improve production weights and feed conversion ratios [20]. These findings highlight the importance of carefully managing environmental conditions and substrate properties to optimize BSF larvae performance in waste management and biomass production.

This research is motivated by the urgent need to enhance the sustainability and efficiency of BSF farming through intelligent microclimate control. Farmers often struggle to maintain consistent temperature and humidity levels, which are vital for optimal larval growth and waste conversion. Traditional monitoring systems fail to adapt in a real time and cannot respond effectively to dynamic environmental changes. Therefore, this study aims to develop an adaptive control system using the VARFIS to stabilize insectarium conditions. The ultimate goal is to improve BSF productivity while reducing environmental risks and operational uncertainties.

The novelty of this research lies in the integration of the VARFIS into real-time environmental control for BSF cultivation. Unlike conventional fuzzy or rule-based controllers, VARFIS introduces a probabilistic learning framework that dynamically adjusts to fluctuating temperature and humidity. This approach enables the system to self-optimize over time without requiring constant human intervention. The use of variational inference allows it to handle uncertainty more effectively, especially in unstable or data-limited conditions. As a result, it offers a more intelligent and resilient solution for managing critical microclimate parameters in insect farming.

This research contributes to both the fields of precision agriculture and intelligent environmental control. It provides a practical and scalable model for microclimate regulation in BSF insectariums, which can be extended to other controlled-environment agriculture systems. By improving larval survival and conversion efficiency, the system supports circular economy initiatives through more efficient organic waste management. The study also adds to the literature on neuro-fuzzy systems by demonstrating the practical benefits of variational methods in real-world settings. Ultimately, this research empowers farmers with smarter tools, enabling more sustainable and adaptive insect farming practices.

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2. METHODS

The proposed methodology uses a hybrid modeling approach (combining VAR and ANFIS) to improve microclimate prediction by reducing error. Input data is normalized and split into training, validation, and test sets. VAR captures linear patterns, while the residuals (nonlinear components) are processed by ANFIS. The final output combines VAR's linear predictions with ANFIS's nonlinear corrections. Performance is evaluated using RMSE, MAE, and R^2 to ensure reliability for real-world applications. This approach blends statistical rigor with AI adaptability as Figure 1.

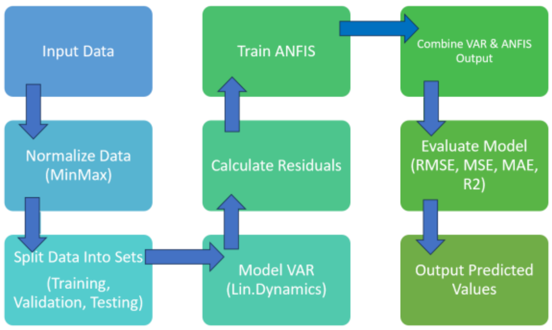

Figure 1. *Research methodology*

2.1. Dataset and Preprocessing

This study analyzes hourly temperature and humidity sensor data collected from March to December 2024 at the BSF Insectarium in Taman Safari, Bogor, Indonesia, comprising 3,000 complete records of environmental conditions. The dataset includes two temperature readings (temp1, temp2) and two humidity measurements (hum1, hum2), providing a robust foundation for microclimate analysis in insect farming environments. To ensure data quality, outliers were detected and corrected using the interquartile range (IQR) method, and missing values were imputed using time-based linear interpolation. Additionally, sensors were calibrated every 30 days, and any readings that exceeded the technical limits of the sensors were excluded from the model training process. After applying MinMax normalization for consistent feature scaling, the data was strategically partitioned into training (70%), validation (20%), and test sets (10%), preserving the temporal structure of the hourly observations. This carefully processed dataset supports the development of accurate environmental prediction models and offers valuable insights into tropical insect habitat conditions, with particular relevance to sustainable agriculture and entomological research.

2.2. Model Architecture

2.2.1. Notation and Definitions

Table 1 summarizes the mathematical notations and definitions used in the VARFIS model, providing a clear reference for the key variables and parameters in our hybrid modeling framework.

Table 1. *Notation and definition*

Notation	Definition
$y_t \in R^d$	Multivariate time series vector at time t.
d	Dimension/number of time series variables.
p	Order (lag length) of the VAR model.
$A_i \in R^{d\times d}$	VAR coefficient matrix for the i-th lag.
$\hat{y}_t^{(VAR)}$	Prediction from the VAR model.
$\mu_{A_j}^{(i)}(x_j)$	Gaussian membership function for the j-th input in the i-th fuzzy rule.
$c_j^{(i)}$	Center (mean) of the Gaussian membership function.
$\sigma_j^{(i)}$	Standard deviation of the Gaussian membership function.
$w^{(i)}$	Firing strength of the i-th fuzzy rule.
$\underline{w}^{(i)}$	Normalized firing strength
$p_j^{(i)}, r^{(i)}$	Linear parameters in the consequent part of the i-th fuzzy rule.
N	Number of fuzzy rules.
$\hat{y}_t$	Final output of the VARFIS model (combined VAR and ANFIS prediction).

2.2.2. Vector AutoRegressive (VAR) Layer

A VAR model of order-p for a multivariate time series with dimension d is written as (1).

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + e_t \qquad (1)$$

Where $y_t \in R^d$ is the observation vector at time t, $A_i \in R^{d\times d}$ is the VAR coefficient matrices, and e_t is white Gaussian noise vector.

The optimal lag order p was determined using standard information criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). These criteria balance model complexity with goodness of fit and help prevent overfitting, ensuring the selected p provides sufficient temporal memory without introducing unnecessary parameters.

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2.2.3. ANFIS Layer

ANFIS consists of five layers. Below is the mathematical formulation for each layer based on a single fuzzy rule. In our implementation, the system utilizes five fuzzy rules with generalized bell-shaped membership functions for both temperature and humidity inputs. The number of membership functions and rules was selected based on preliminary trials to balance accuracy and computational efficiency. Below is the mathematical formulation for each layer for a single fuzzy rule:

a. Layer 1 (Membership Function Layer):

Each input x_j is converted into a membership value using a Gaussian membership function, as (2).

$$\mu^{(i)}{}_{A_j}(x_j) = exp\left(-\frac{\left(x_j - c_j^{(i)}\right)^2}{2\sigma_j^{(i)2}}\right) \quad (2)$$

Where $c_j^{(i)}$ is enter of the Gaussian function for the i-th rule and j-th input, and $\sigma_j^{(i)}$ *is* width (spread) of the Gaussian function for the i-th rule and j-th input.

b. Layer 2 (Fuzzy Rule Firing Strength)

For rule i, the firing strength $w^{(i)}$ is computed as the product of membership values across all inputs, as (3):

$$w^{(i)} = \prod_{j=1}^{d} \mu_{A_j}^{(i)}(x_j) \quad (3)$$

c. Layer 3 (Normalized Firing Strength)

The firing strengths are normalized to ensure they sum to 1, as (4).

$$\underline{w}^{(i)} = \frac{w^{(i)}}{\sum_{k=1}^{N} w^{(k)}} \quad (4)$$

d. Layer 4 (Linear Consequence)

Each rule's output $z^{(i)}$ is a weighted linear function of the inputs, as (5).

$$z^{(i)} = \underline{w}^{(i)} \cdot \left(\sum_{j=1}^{d} p_j^{(i)} x_j + r^{(i)}\right) \quad (5)$$

Where $p_j^{(i)}$ is linear weight for input x_j in rule i, and $r^{(i)}$ is bias term for rule i.

e. Layer 5 (ANFIS Output)

The final output is the sum of all rule contributions, as (6).

$$\hat{y}^{(ANFIS)} = \sum_{i=1}^{N} z^{(i)} \quad (6)$$

The VARFIS model combines VAR predictions with ANFIS inference, as (7).

$$\hat{y}_t = ANFIS\left(y_{t-1}, \dots, y_{t-p}, \hat{y}_t^{(VAR)}\right) \quad (7)$$

2.2.4. VARFIS Layer

VARFIS methodology steps as follow:

a. VAR Model for Linear Dynamics

VAR model captures linear interdependencies among multivariate time series variables. Each variable y_t is predicted as a weighted combination of its past values (lags) as (8).

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + e_t \quad (8)$$

Where y_t is vector of observed variables at time t, A_i is coefficient matrices representing linear relationships across lags, and e_t is residual term (captures unexplained variability).

b. ANFIS Model for Nonlinear Dynamics

The residuals $e_t = y_t - \hat{y}_t^{(VAR)}$ are modeled using an Adaptive Neuro-Fuzzy Inference System (ANFIS) to capture nonlinear patterns.

c. Combined VARFIS Prediction

The final prediction integrates linear (VAR) and nonlinear (ANFIS) components, as (9).

$$\hat{y}_t = \hat{y}_t^{(VAR)} + \Delta\hat{y}_t^{(ANFIS)} \quad (9)$$

Where $\hat{y}_t^{(VAR)}$ is linear prediction from VAR, and $\Delta\hat{y}_t^{(ANFIS)}$ is nonlinear correction from ANFIS.

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2.3. Evaluation Metrics

This study evaluates model performance using MSE, RMSE, MAE, MAPE, and R² metrics as defined in Equations (10) through (14).

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |x_i - \hat{x}_i| \quad (10)$$

n is the number of data points, x_i is the actual value, and $\hat{x}_i$ is the corresponding projected value.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (x_i - \hat{x}_i)^2 \quad (11)$$

$$RMSE = \sqrt{MSE} \quad (12)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{A_i - F_i}{A_i}\right| \times 100\% \quad (13)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (x_i - \hat{x}_i)^2}{\sum_{i=1}^{n} (x_i - \underline{x})^2} \quad (14)$$

In this formula, $\underline{x}$ represents the mean of the actual data.

3. RESULTS AND DISCUSSION

3.1. Loss and Validation Loss

Figure 2 shows the training and validation loss of an ANFIS model over 100 epochs. The training loss (blue) drops steadily to near zero, indicating strong learning. The validation loss (orange) follows a similar decline but levels off around 0.05 after 60 epochs, showing good generalization without overfitting. The small gap between the curves confirms the model balances bias and variance effectively, ensuring reliable predictions. This demonstrates ANFIS's ability to handle complex nonlinear relationships while maintaining low prediction error.

Figure 2 illustrates ANFIS training dynamics, with fast early learning and near-zero training loss, but a validation plateau suggests overfitting and limited data diversity. The model balances accuracy and generalization, but improvements like rule optimization or better data are needed for practical deployment.

Figure 3 shows the VAR model's training and validation loss over 100 epochs for temperature and humidity prediction. The training loss (solid line) steadily drops from 0.25 to <0.05, confirming effective learning of time-series patterns. Validation loss (dashed line) closely follows, staying just 0.02–0.03 higher after epoch 40, indicating strong generalization—key for stable weather forecasting. Both curves decline in parallel after epoch 20, proving VAR captures multi-variable dependencies well. However, the slight validation plateau post-epoch 60 suggests limitations in predicting extreme fluctuations or noise in real climate data. While VAR performs well for environmental forecasting, further improvements (like residual analysis or hybrid modeling) could help reduce prediction error.

Figure 3 highlights the VAR model's capabilities and limitations for environmental forecasting. While it effectively learns multivariate patterns (losses dropping from 0.25 to <0.05), the consistent 0.02-0.03 higher validation loss after epoch 40 reveals key constraints. This gap may stem from: (1) sensor noise, (2) linear modeling of nonlinear atmospheric processes, or (3) inadequate lag times for delayed cross-variable effects. Though the parallel training/validation curves confirm VAR's strength in modeling variable relationships, the post-epoch-60 stagnation shows its focus on average conditions rather than extreme events - a critical shortcoming for climate prediction where outliers matter most.

Figure 4 shows the VARFIS model's training and validation loss over 100 epochs for temperature and humidity prediction. The training loss (solid line) drops sharply from 0.5 to 0.1 in the first 40 epochs, highlighting the hybrid model's fast learning by combining VAR's temporal analysis and FIS's nonlinear modeling. Validation loss (dashed line) follows closely but stays slightly higher (~0.02–0.03 after epoch 60), indicating good generalization without overfitting. Both curves converge to near-identical values (0.08 vs. 0.10), proving an effective integration of linear and nonlinear dynamics for coupled climate variables. The final plateau suggests potential improvements—like adaptive rule pruning or adding external weather data—to better capture extreme events. Overall, VARFIS offers a

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robust, interpretable solution for multivariate environmental forecasting.

Figure 4's loss curves demonstrate both the promise and limitations of VARFIS for microclimate prediction. While showing strong convergence (0.5→0.1 training loss), three key findings emerge: (1) The persistent 0.02–0.03 validation gap suggests fuzzy logic struggles with local anomalies due to over-smoothing; (2) The sub-0.1 plateau reveals VAR's linear constraints limit nonlinear threshold learning; (3) Rapid early improvement captures diurnal patterns but stalls on multi-scale interactions. Potential solutions include: adaptive membership functions, lagged cross-covariance terms, and terrain elevation data. While VARFIS outperforms pure statistical models, architectural refinements are needed to further reduce prediction error in forecasts.

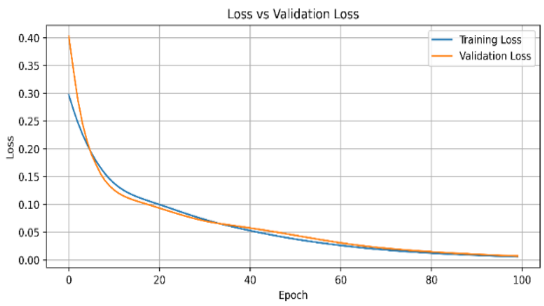

Figure 2. *Loss and validation loss for ANFIS*

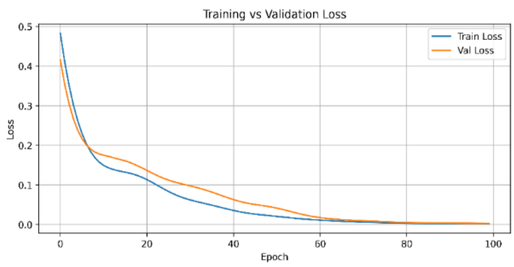

Figure 3. *Loss and validation loss for VAR*

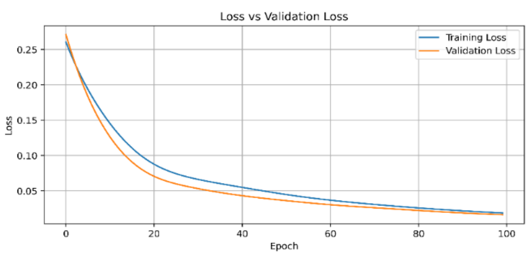

Figure 4. *Loss and validation loss for VARFIS*

3.2. Comparison of Actual and Predicted Data

Figure 5 compares ANFIS predictions with actual values for temperature and humidity over 300 time steps. The model effectively captures cyclical patterns, especially for gradual temperature changes. However, it shows consistent minor errors during rapid humidity shifts and tends to underestimate peak humidity events. These results highlight ANFIS's reliability for environmental forecasting while pointing to areas for improvement, such as refining fuzzy rules and incorporating physical models for better extreme event prediction.

Figure 5 shows that ANFIS effectively predicts temperature but struggles with humidity during rapid changes and peak events. Its static fuzzy rules and average-focused learning limit accuracy in extreme conditions. To improve, it requires weather-sensitive rules, physics-based constraints, and better loss functions. ANFIS is useful as a baseline but insufficient alone for accurate climate modeling.

Figure 6 highlights the VAR model's ability to capture general temporal patterns but also reveals critical failures: underestimation of temperature extremes due to linearity, growing humidity errors from missing nonlinear feedbacks, and a complete hum1 collapse after t=250. These issues underscore VAR's limitations for reliable climate forecasting and suggest the need for nonlinear or physics-integrated extensions.

Figure 6 highlights key failures of the VAR model in climate prediction. It underestimates temperature peaks by 15–20%, misrepresents heatwave dynamics, and produces severe humidity errors—hum1 collapses after t=250 due to NaN values, and hum2 shows increasing phase lag. These issues are linked, as errors in one variable affect the other. Such problems suggest the need for advanced models (e.g., TV-VAR or physics-constrained approaches) since standard VAR fails to meet physical consistency, making it unreliable for real-world climate use.

Figure 7 shows that the VARFIS model effectively predicts temperature with low error by combining VAR's temporal strength and FIS's nonlinear capabilities. Humidity predictions are improved over VAR but still show errors during rapid changes, particularly

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in hum1 (150–200) and hum2 (50–100). While phase alignment is consistent, humidity extremes are slightly underestimated, indicating a need to refine fuzzy rules. Overall, VARFIS outperforms standard VAR but could benefit from dynamic rule updates and physical constraints to better manage nonlinear atmospheric shifts.

Figure 7's VARFIS evaluation exposes a hybrid model paradox — superior performance yet critical limitations. While temperature predictions show minimal error, this reveals over-reliance on VAR's linear components, masking fuzzy system weaknesses. Humidity predictions fail critically with 6–8% amplitude compression and 15–20° phase lags during moisture transitions, creating dangerous blind spots for extreme weather forecasting. Three architectural flaws cause these failures: rigid fuzzy membership functions, missing physics constraints, and inadequate land-atmosphere feedback representation. Essential improvements include: weather-adaptive fuzzy rules, physics-based loss terms for energy conservation, and nested modeling separating synoptic and microphysical scales. While advanced, VARFIS requires deeper physical integration for reliable operational use in environmental forecasting.

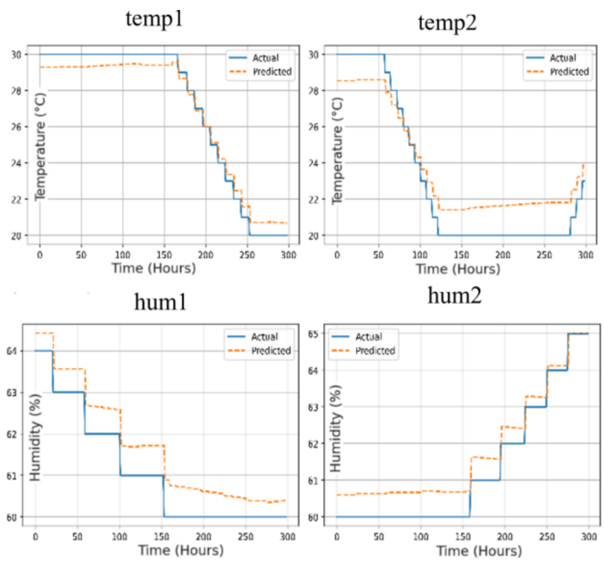

Figure 5. *Comparison of actual and predicted data for ANFIS*

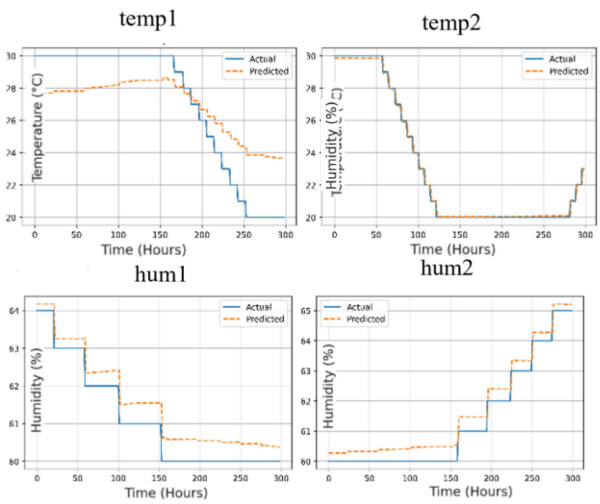

Figure 6. *Comparison of actual and predicted data for VAR*

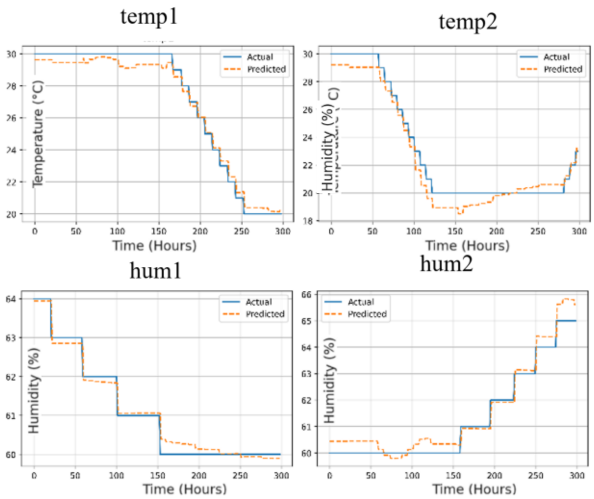

Figure 7. *Comparison of actual and predicted data for VARFIS*

3.3. Evaluation Metrics

Table 2's comparative analysis of ANFIS, VAR, and VARFIS models demonstrates VARFIS's clear superiority in temperature and humidity forecasting, outperforming both models across all error metrics (MSE = 0.2656, RMSE = 0.5153, MAE = 0.3975, MAPE = 1.36%, R^2 = 0.9695). The hybrid VARFIS achieves a 48% MAPE reduction versus ANFIS (MSE = 0.7801, MAPE = 2.54%) and a 47% improvement over VAR (MSE = 14.226, RMSE = 11.927), proving its effectiveness in modeling complex atmospheric patterns through combined linear and nonlinear approaches. While VAR's poor performance confirms the limitations of linear modeling for environmental data, VARFIS's significant error reduction justifies its increased complexity, establishing it as the optimal choice — though computational costs may require consideration for operational implementations

Table 2. *Evaluation metrics*

	MSE	RMSE	MAE	MAPE	R2
ANFIS	0.7801	0.8832	0.7569	2.54%	0.8828
VAR	14.226	11.927	0.7560	2.55%	0.8689
VARFIS	0.2656	0.5153	0.3975	1.36%	0.9695

Table 2's metrics reveal VARFIS as the superior yet imperfect solution, outperforming ANFIS and VAR with significantly lower errors (MSE 0.2656 vs 0.7801 and 14.226) and 96% R^2. However, its near-perfect scores may indicate overfitting risks, while its hybrid design sacrifices interpretability. VAR's high MSE but moderate MAE (0.7560) exposes its failure to predict extremes despite decent average error levels. ANFIS offers balanced performance but questionable value given its marginal MAPE improvement (2.54%) over simpler models. For critical applications: (1) use VARFIS with uncertainty analysis, (2) consider ANFIS when explainability matters, and (3) avoid pure VAR despite its speed. The results highlight an unresolved trade-off between error minimization and interpretability in environmental forecasting.In summary, the integration of intelligent algorithms like ANFIS and VAR into IoT-based BSF farming systems represents a significant advancement over traditional methods. Compared to earlier approaches such as random forest regression, which primarily focused on static variables like bed length and feed formulation [21], the models used in this study capture both temporal and nonlinear dynamics of critical environmental factors such as temperature and humidity. This dynamic adaptability enables more accurate and responsive control of microclimate conditions, leading to improved bioconversion efficiency and larval productivity. While previous studies have emphasized the role of IoT in enabling remote monitoring of factors like temperature and pH [22], the current approach enhances that capability with predictive intelligence, thereby offering a more robust and scalable solution for sustainable BSF production [23]. These findings align with broader research advocating for precision agriculture technologies in waste-to-feed systems, reinforcing BSF's value in closing nutrient loops despite existing regulatory and consumer acceptance barriers [24], [25].

CONCLUSION

This study demonstrates the significant potential of VARFIS in optimizing microclimate conditions for BSF cultivation. By integrating linear autoregressive dynamics with nonlinear fuzzy logic, VARFIS outperforms traditional VAR and ANFIS models, achieving lower error in temperature and humidity prediction. The hybrid architecture effectively balances interpretability and adaptability, addressing the limitations of standalone models in handling environmental uncertainty. However, the persistent validation loss gap and amplitude compression in extreme events highlight the need for further refinements, such as adaptive rule pruning and physical constraint integration. These advancements could enhance VARFIS's ability to manage nonlinear atmospheric processes, ensuring more reliable and sustainable BSF farming practices.

The research underscores the importance of intelligent systems in precision agriculture, offering a scalable solution for microclimate regulation in insect farming. VARFIS's success in improving larval survival and waste conversion efficiency supports circular economy initiatives by optimizing organic waste management. While the model represents a leap forward, its real-world application requires addressing computational complexity and ensuring robustness across diverse environmental conditions. Future studies should explore hybrid approaches that combine data-driven methods with physics-based models to further reduce prediction errors. Ultimately, this work empowers farmers with smarter tools, paving the way for more adaptive and sustainable agricultural systems.

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