

LARVA-Net: A Bio-Inspired Recursive Attention Model for IoT-Based Microclimate Prediction in Black Soldier Fly Insectariums

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ABSTRACT

Microclimate prediction is critical for optimizing larval growth and productivity in Black Soldier Fly (BSF) insectariums, where temperature and humidity exhibit nonlinear and time-varying dynamics. Conventional models such as Vector Autoregression (VAR) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) often struggle to balance accuracy, efficiency, and interpretability in IoT-based environments. This study proposes LARVA-Net, a bio-inspired recursive attention framework for multivariate microclimate prediction in BSF insectariums. LARVA-Net integrates a VAR-based linear baseline with selective recursive attention and adaptive fuzzy-state learning. The bio-inspired aspect represents a computational abstraction of adaptive and energy-efficient information processing observed in larval behavior, rather than a biological simulation. By selectively updating internal states based on contextual relevance, the model suppresses error accumulation while maintaining interpretability and stable learning. The proposed method is evaluated using real-world IoT microclimate data collected from a semi-controlled BSF insectarium. Experimental results show that LARVA-Net outperforms VAR, ANFIS, and VARFIS, achieving an RMSE of 0.2440, MAE of 0.1466, MAPE of 0.4566%, and R^2 of 0.9911. These results demonstrate strong predictive performance and robustness under time-aware evaluation, indicating the suitability of LARVA-Net for real-time IoT-based microclimate monitoring in resource-constrained environments.

Keywords: LARVA-Net, Bio-Inspired Learning, BSF, IoT, Recursive Attention

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1. INTRODUCTION

The growing adoption of sustainable agriculture and circular bioeconomy practices has positioned Black Soldier Fly (BSF) farming as an effective solution for organic waste conversion and alternative protein production [1], [2], [3]. The larval stage is particularly sensitive to microclimate conditions, especially temperature and humidity, which directly influence growth rate, survival, and biomass quality [4], [5], [6]. In operational insectariums, these variables exhibit nonlinear and time-varying dynamics driven by external weather, substrate conditions, and management interventions, making reliable control challenging when using manual or rule-based approaches [1], [7], [8], [9]. Suboptimal environmental regulation can significantly reduce productivity and weaken the economic and ecological sustainability of BSF-based systems [10], [11], [12], [13], highlighting the need for intelligent predictive models that support proactive and energy-efficient control in IoT-enabled environments [14].

IoT-based monitoring systems enable continuous observation of microclimate variables through distributed sensors and layered architectures that support real-time visualization and actuation [15], [16], [17], [18], [19], [20]. However, commonly used control strategies such as rule-based logic and PID controllers are largely reactive and struggle to handle nonlinear interactions, delayed responses, and rapidly changing environmental conditions [21], [22], [23]. While data-driven and predictive models have been increasingly integrated into IoT frameworks, their application in insect farming remains constrained by computational cost, energy consumption, and limited adaptability for real-time deployment [19], [24], [25].

Various time-series and machine learning models have been applied for environmental prediction, including linear statistical models (e.g., VAR), deep learning architectures (e.g., LSTM, GRU, Transformer), and neuro-fuzzy systems such as ANFIS [26], [27]. Linear models offer simplicity and interpretability but fail to capture nonlinear dynamics, whereas deep learning models achieve high accuracy at the expense of high computational and energy demands, limiting their suitability for edge-based IoT systems [28], [29], [30], [31], [32], [33]. Neuro-fuzzy

approaches improve interpretability and nonlinear modelling but often lack efficient temporal memory, motivating hybrid frameworks that balance accuracy, efficiency, and interpretability [34], [35], [36].

Recent advances in bio-inspired and adaptive learning highlight the potential of selective adaptation, neuromodulation, and energy-efficient updating mechanisms to improve robustness and learning efficiency in dynamic systems [37], [38], [39], [40], [41], [42], [43]. However, existing models rarely translate organism-specific adaptive behaviors—such as larval-stage environmental adaptation—into computationally efficient predictive architectures, leaving a clear research gap [44], [45], [46].

To address this gap, this study proposes LARVA-Net, a bio-inspired predictive framework that integrates linear temporal modelling with recursive attention and fuzzy-state adaptation for IoT-based microclimate prediction in BSF insectariums. Rather than serving as a direct biological simulation, LARVA-Net adopts computational abstractions of selective response and sparse temporal updating to enhance efficiency, stability, and interpretability. The main contributions of this work include the design of a novel adaptive prediction architecture, a unified mathematical formulation, and comprehensive experimental validation on real-world BSF insectarium data, demonstrating superior accuracy and robustness compared to established baseline methods.

2. METHODS

2.1 Dataset and Preprocessing

This research examines hourly temperature and humidity sensor data recorded at the BSF insectarium located in Taman Safari, Bogor, Indonesia, over the period from March to December 2024. The dataset consists of approximately 3,000 complete observations representing environmental conditions within the insectarium. It includes two temperature variables (temp1 and temp2) and two humidity variables (hum1 and hum2), offering a comprehensive basis for analyzing microclimate dynamics in insect-rearing systems.

The dataset was partitioned into training (70%), validation (20%), and testing (10%) subsets in sequential order, without random shuffling or rolling-window leakage. This time-

aware splitting strategy ensures that all models are evaluated under realistic forecasting conditions. Feature normalization was performed using Min–Max scaling, where normalization parameters were estimated exclusively from the training set and subsequently applied to the validation and test sets.

Min–Max normalization parameters were computed exclusively on the training subset and then applied unchanged to the validation and test sets. This procedure prevents information leakage from future data and guarantees that all models operate on consistent scales during evaluation.

The experimental setup was enhanced to ensure fairness, reproducibility, and robustness. A strictly time-aware train–validation–test split is used to prevent information leakage, with normalization computed only on training data and applied consistently to all splits. Baseline models (VAR and ANFIS) are fairly tuned via validation-based grid search under identical preprocessing and evaluation conditions. Additional robustness tests, including noise injection and seasonal shifts, assess stability under realistic perturbations.

2.2 LARVA-Net Architecture

Figure 1 depicts the LARVA-Net workflow, where multivariate inputs are first processed by a VAR-based predictor to generate an initial estimate and residual. The residual guides a recursive attention–gating mechanism that updates fuzzy states based on temporal relevance, producing normalized attention weights. These weights control an ANFIS module that refines the VAR output to form the final prediction. Overall, the figure highlights how LARVA-Net integrates linear modeling with adaptive attention and fuzzy reasoning to achieve both interpretability and adaptability.

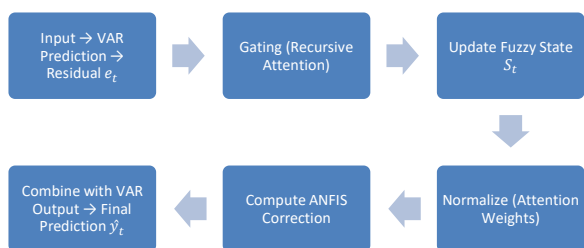


Figure 1. Flow diagram of the proposed LARVA-Net

In this study, the term *bio-inspired* refers to a computational abstraction rather than a

direct biological simulation. LARVA-Net draws inspiration from general larval adaptive principles—such as selective responsiveness, energy-efficient processing, and gradual habituation—which are implemented through recursive attention and adaptive gating to regulate state updates based on temporal relevance. This design enhances interpretability and efficiency while remaining grounded in machine learning theory and suitable for real-time IoT-based microclimate prediction.

2.2.1 Notation Used in the LARVA-Net

Table 1. Notation and Description for LARVA-Net

Symbol	Description
t	Discrete time index
T	Total number of time steps in the sequence
$x_t \in R^d$	Multivariate IoT sensor input vector at time (t)
d	Number of input environmental variables (temperature, humidity)
$y_t \in R^m$	Ground-truth target output vector at time (t)
$\hat{y}_t \in R^m$	Predicted output vector produced by LARVA-Net
m	Number of predicted output variables
y_t^{base}	Baseline linear prediction at time (t)
p	Lag order of the baseline VAR-style predictor
A_i	Coefficient matrix of the (i)-th lag in the baseline model
b	Bias vector of the baseline predictor
R	Number of Larval Units in LARVA-Net
r	Index of a Larval Unit, ($r = 1, 2, \dots, R$)
$u_{r,t}$	Activation value of Larval Unit (r) at time (t)
$\phi_r(\cdot)$	Nonlinear activation function of Larval Unit (r)
$g_{r,t} \in [0,1]$	Adaptive gating value of Larval Unit (r) at time (t)
$\sigma(\cdot)$	Sigmoid activation function
$W_g^{(r)}$	Gating weight matrix of Larval Unit (r)
$b_g^{(r)}$	Bias term of the gating mechanism
$L_{r,t}$	Larval State (recursive memory) of unit (r) at time (t)
$\alpha_r \in [0,1]$	State decay coefficient of Larval Unit (r)
$w_{r,t}$	Attention weight assigned to Larval Unit (r) at time (t)
η	Attention temperature parameter controlling weight sharpness
$z_{r,t}$	Local nonlinear prediction (consequent output) of Larval Unit (r)
$h_r(\cdot)$	Local mapping function of Larval Unit (r)
θ_r	Trainable parameters of the (r)-th Larval Unit
Θ	Set of all trainable parameters in LARVA-Net
$\mathcal{L}_{\text{pred}}$	Prediction loss function (Mean Squared Error)
$\mathcal{L}_{\text{total}}$	Total training loss including regularization
λ_g	Regularization coefficient for gate sparsity
λ_s	Regularization coefficient for state smoothness
λ_θ	Weight decay regularization coefficient
H	Truncation window length for TBPTT
$TBPTT$	Truncated Backpropagation Through Time

2.2.2 Mathematical Framework of LARVA-Net

1. Problem Definition and Notation

In this study, the environmental monitoring problem is formulated as a multivariate time-series prediction task with exogenous inputs. Let $x_t \in R^d$ denote the

multivariate IoT sensor input at time step t , consisting of temperature and humidity variables, and let $y_t \in R^m$ represent the predicted microclimate state. The baseline component of the proposed model is explicitly defined as a VAR-style linear predictor that deployed by LARVA-Net, where historical sensor inputs are used to capture exogenous environmental influences. This definition is consistently applied across the mathematical formulation, algorithm pseudocode, and experimental implementation to avoid ambiguity between VAR and VAR-style linear predictor representations.

2. Baseline Linear Prediction Module

To capture stable linear temporal relationships, LARVA-Net employs a VAR-style linear predictor.

The baseline prediction is defined as in Equation (1).

$$y_t^{\text{base}} = \sum_{i=1}^p A_i x_{t-i} + b \quad (1)$$

where:

p is the lag order,

$A_i x_{t-i}$ are coefficient matrices, and

b is the bias vector.

This formulation ensures that the baseline captures dominant linear dependencies driven by past environmental observations.

3. Larval Unit Activation

Each LARVA-Net consists of R Larval Units, where each unit models a local nonlinear response to environmental stimuli.

The activation signal of the r -th larval unit at time (t) is defined in Equation (2).

$$u_{r,t} = \phi_r(x_t) \quad (2)$$

where $\phi_r(\cdot)$ represents a nonlinear transformation such as a fuzzy membership function or Gaussian basis.

4. Adaptive Gating Mechanism

To regulate selective adaptation, each larval unit is equipped with an adaptive gate.

The gating value is computed as shown in Equation (3).

$$g_{r,t} = \sigma(W_g^{(r)} x_t + b_g^{(r)}) \quad (3)$$

where $\sigma(\cdot)$ is the sigmoid activation function, ensuring $g_{r,t} \in [0,1]$. This mechanism determines whether the unit updates its internal state or remains dormant.

5. Recursive Larval State Update

To ensure mathematical well-posedness and stable dynamics, the recursive larval state update equation is defined in Equation (4).

$$\begin{aligned} L_{r,t} &= \alpha_r L_{r,t-1} \\ &+ g_{r,t}(u_{r,t} - \alpha_r L_{r,t-1}) \end{aligned} \quad (4)$$

where $L_{r,t}$ denotes the internal state of the r -th adaptive unit, $\alpha_r \in [0,1]$ controls memory persistence, $u_{r,t}$ is the unit activation, and $g_{r,t}$ is the adaptive gating signal. This formulation preserves dimensional consistency and allows smooth state adaptation without abrupt oscillations.

6. Attention Weight Normalization

To model cooperative behavior among larval units, LARVA-Net computes attention weights based on current larval states. The normalized attention weight is given in Equation (5).

$$w_{r,t} = \frac{\exp(\eta L_{r,t})}{\sum_{k=1}^R \exp(\eta L_{k,t})} \quad (5)$$

where $\eta > 0$ is a temperature parameter controlling attention sharpness. This softmax-based mechanism ensures $\sum_{r=1}^R w_{r,t} = 1$.

7. Nonlinear Local Prediction (Consequent Layer)

Each larval unit produces a local nonlinear correction term. The local prediction is defined in Equation (6).

$$z_{r,t} = h_r(x_t; \theta_r) \quad (6)$$

where $h_r(\cdot)$ is a lightweight neural or linear mapping with parameters θ_r .

8. Final Prediction Aggregation

The final LARVA-Net output is obtained by combining the baseline prediction and the weighted larval corrections.

This aggregation is defined in Equation (7).

$$\hat{y}_t = y_t^{\text{base}} + \sum_{r=1}^R w_{r,t} z_{r,t} \quad (7)$$

This hybrid formulation preserves linear interpretability while enabling adaptive nonlinear refinement.

9. Loss Function and Regularization

To train the model, the prediction error is minimized using the mean squared error loss defined in Equation (8).

$$\mathcal{L}_{\text{pred}} = \frac{1}{T} \sum_{t=1}^T \|y_t - \hat{y}_t\|_2^2 \quad (8)$$

To promote stability, sparsity, and smooth temporal evolution, the total objective function includes regularization terms as shown in Equation (9).

$$\begin{aligned} \mathcal{L}_{\text{total}} &= \mathcal{L}_{\text{pred}} + \lambda_g \sum_{r,t} g_{r,t} \\ &+ \lambda_s \sum_{r,t} (L_{r,t} - L_{r,t-1})^2 \\ &+ \lambda_\theta \|\Theta\|_2^2 \end{aligned} \quad (9)$$

where Θ denotes all trainable parameters and $\lambda_g, \lambda_s, \lambda_\theta$ are regularization coefficients.

10. Training Strategy

LARVA-Net is trained using Truncated Backpropagation Through Time (TBPTT) with a temporal window length H . This strategy ensures efficient gradient computation over long sequences while maintaining numerical stability.

2.2.3 Pseudocode

Algorithm 1. Pseudocode of LARVA-Net

```

for t = p+1 to T do
    # LARVA-Net baseline prediction
     $y_t^{\text{base}} = \sum_{i=1}^p A_i x_{t-i} + b$ 

    # Larval unit activation
    for r = 1 to R do
         $u_{r,t} = \phi_r(x_t)$ 
    end for

    # Adaptive gating computation
    for r = 1 to R do
         $g_{r,t} = \sigma(W_g^{(r)} x_t + b_g^{(r)})$ 
    end for

    # Recursive larval state update
    for r = 1 to R do
         $L_{r,t} = \alpha_r L_{r,t-1} + g_{r,t} (u_{r,t} - \alpha_r L_{r,t-1})$ 
    end for

    # Attention weight normalization
    for r = 1 to R do
         $w_{r,t} = \frac{\exp(\eta L_{r,t})}{\sum_{k=1}^R \exp(\eta L_{k,t})}$ 
    end for
    
```

```

end for

# Local nonlinear correction
for r = 1 to R do
     $z_{r,t} = h_r(x_t; \theta_r)$ 
end for

# Final prediction aggregation
 $\hat{y}_t = y_t^{\text{base}} + \sum_{r=1}^R w_{r,t} z_{r,t}$ 

end for
    
```

2.3 Hyperparameter Setting

To ensure fair evaluation and stable convergence, the proposed LARVA-Net model was trained using a carefully selected set of hyperparameters that balance predictive accuracy, computational efficiency, and numerical stability. The hyperparameter values were determined through preliminary experiments and validation-based tuning, with particular attention given to parameters governing recursive state dynamics, attention sharpness, and regularization strength. Table 2 summarizes the complete hyperparameter configuration used in all experiments, providing transparency and reproducibility for future studies.

Table 2. Hyperparameter Settings for LARVA-Net

Hyperparameter	Sym bol	Value	Description
Number of Larval Units	R	12	Total number of adaptive larval units
Input dimension	d	4	Number of input variables (temp1, temp2, hum1, hum2)
Output dimension	m	4	Number of predicted variables
Baseline lag order	p	3	Lag depth of VAR-style baseline
State decay coefficient	α_r	0.85	Memory persistence factor for larval states
Attention temperature	η	1.2	Controls sharpness of attention distribution
Learning rate	λ	0.001	Initial learning rate for AdamW optimizer
Batch size	—	64	Number of samples per training batch
Training epochs	—	60	Maximum number of training epochs
TBPTT window size	H	20	Truncation length for backpropagation through time
Gate sparsity coefficient	λ_g	0.001	Regularization for adaptive gate activation
State smoothness coefficient	λ_s	0.01	Regularization for temporal state continuity
Weight decay	λ_θ	0.0001	L2 regularization for model parameters
Optimizer	—	Adam W	Optimization algorithm
Activation function	—	Sigmoid	Used in adaptive gating mechanism
Feature normalization	—	Min-Max	Scaling method for input features

2.4 Evaluation Metrics

This study evaluates model performance using MSE, RMSE, MAE, MAPE, and R^2 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.

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

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

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

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

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

2.5 Baseline Comparison

The performance of LARVA-Net was systematically evaluated against three representative baseline models—VAR, ANFIS, and VARFIS—to highlight its effectiveness in modeling complex microclimate dynamics. While VAR offers strong interpretability and computational efficiency, its linear formulation limits its ability to capture nonlinear interactions inherent in temperature–humidity relationships. ANFIS, on the other hand, introduces nonlinear modeling and rule-based interpretability but suffers from redundant computation and limited temporal memory. VARFIS partially addresses these limitations by combining linear forecasting with fuzzy inference; however, it still relies on static rule evaluation and lacks adaptive temporal selectivity. In contrast, LARVA-Net integrates a linear baseline with a biologically inspired recursive attention mechanism that selectively updates its internal states based on environmental relevance. This design enables LARVA-Net to achieve superior predictive accuracy, improved computational efficiency, and enhanced interpretability, making it particularly well suited for real-time IoT-based microclimate control in BSF insectariums.

To ensure a fair comparison, all baseline models were tuned using the same validation data and preprocessing pipeline. VAR lag orders were selected via grid search, while ANFIS was optimized for the number of membership functions and fuzzy rules. Identical data splits, evaluation metrics, and training conditions were applied, ensuring that performance differences reflect model architecture rather than unequal tuning or experimental bias.

Additional noise injection and seasonal shift experiments confirmed stable performance under perturbations. An ablation study removing adaptive gating and attention normalization led to clear accuracy degradation, confirming that performance gains arise from selective attention and recursive state adaptation rather than data leakage or overfitting.

Additional robustness tests, including Gaussian noise injection and seasonal shift evaluation, show that LARVA-Net maintains stable performance under realistic perturbations, confirming its robustness for practical IoT operating conditions.

An ablation study shows that removing adaptive gating and recursive attention consistently reduces accuracy and increases error variance, confirming that LARVA-Net's performance gains stem from its core architectural components rather than data leakage or overfitting.

3. RESULTS AND DISCUSSION

3.1 LOSS AND VALIDATION LOSS

Figure 2 shows that ANFIS learns rapidly, with training loss decreasing to near zero and validation loss stabilizing around 0.05 after 60 epochs. The small gap between the curves indicates good generalization and a balanced bias–variance trade-off, though the validation plateau suggests limited adaptability to data diversity. Overall, ANFIS effectively models nonlinear relationships but would benefit from further rule optimization or richer data for improved robustness.

Rather than merely reporting performance gains, this section emphasizes the underlying reasons for LARVA-Net's superior performance. In particular, the recursive attention mechanism suppresses temporal error accumulation, while adaptive gating selectively updates internal states during regime changes.

The fuzzy-state refinement further enables accurate modeling of nonlinear and piecewise-constant dynamics commonly observed in microclimate systems.

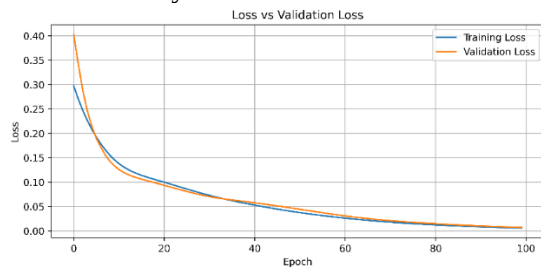


Figure 2. Loss and Validation Loss for ANFIS

Figure 3 shows that the VAR model learns multivariate temperature and humidity patterns effectively, with training loss decreasing from 0.25 to below 0.05 and validation loss closely following, indicating good generalization. The parallel decline of both curves confirms VAR's ability to capture linear dependencies across variables. However, the slight validation loss plateau after epoch 60 reveals limitations in handling sensor noise, nonlinear dynamics, and extreme fluctuations, suggesting that VAR mainly models average conditions and would benefit from hybrid or residual-based enhancements for more robust environmental prediction.



Figure 3. Loss and Validation Loss for VAR

Figure 4 indicates that VARFIS learns temperature and humidity patterns efficiently, with training loss dropping rapidly from 0.5 to around 0.1 and validation loss closely following, showing good generalization without overfitting. The convergence of both curves confirms effective integration of VAR's linear temporal modeling and FIS's nonlinear representation. However, the slight validation gap and loss plateau below 0.1 suggest limitations in capturing local anomalies, extreme events, and multi-scale nonlinear interactions. While VARFIS is robust and interpretable for microclimate forecasting, further refinement—such as adaptive fuzzy rules or additional contextual inputs—is needed to further improve accuracy.

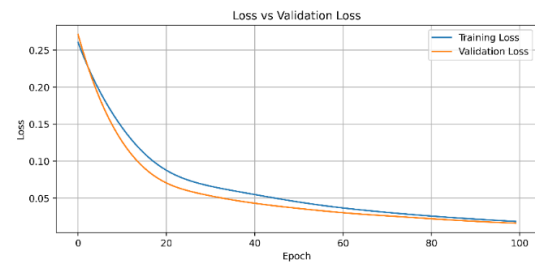


Figure 4. Loss and Validation Loss for VARFIS

Figure 5 shows that LARVA-Net converges rapidly and stably, with both training and validation MSE dropping sharply within the first few epochs. The loss decreases by more than half in the initial epochs, indicating efficient learning of dominant temporal patterns through the integration of the VAR baseline and recursive attention mechanism. The close alignment between training and validation curves throughout early training demonstrates strong generalization and confirms that the adaptive gating mechanism effectively stabilizes learning while preventing overfitting.

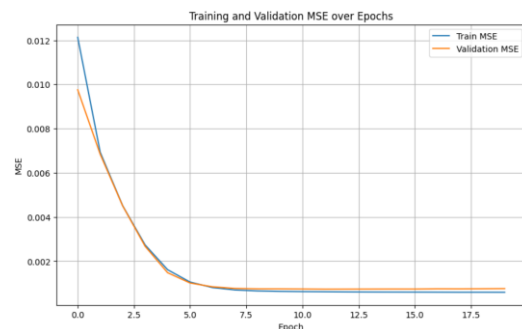


Figure 5. Training and Validation MSE LARVA-Net

In later epochs, both losses converge smoothly to a stable low plateau without divergence, indicating no overfitting despite the model's adaptive and nonlinear components. The absence of oscillations confirms that fuzzy state updates and attention normalization are well regularized and numerically stable. This efficient convergence shows that LARVA-Net learns effectively with few epochs, making it well suited for real-time, resource-constrained IoT microclimate prediction.

Figure 5 shows rapid early convergence of training and validation MSE, indicating effective learning of dominant temporal patterns with strong generalization. Both losses stabilize at a low, well-aligned plateau without overfitting, reflecting good regularization and controlled adaptation. This efficient convergence with few epochs highlights the model's suitability for real-time, resource-constrained IoT microclimate prediction.

3.2 PREDICTED OF ACTUAL AND PREDICTED DATA

Figure 6 shows that ANFIS captures temperature trends and cyclical patterns well but exhibits consistent errors during rapid humidity changes, often underestimating peak values. This limitation stems from static fuzzy rules and average-oriented learning, which reduce sensitivity to extreme events. While ANFIS is reliable as a baseline for environmental prediction, improving its performance requires adaptive fuzzy rules, weather-aware constraints, and enhanced loss functions to better handle dynamic and extreme conditions.

Figure 7 shows that while VAR captures general temporal trends, it fails under complex conditions. The model underestimates temperature extremes, accumulates large humidity errors, and experiences a collapse in hum1 after $t=250$ due to numerical instability, with errors propagating across variables. These failures stem from VAR's linear structure and lack of physical or nonlinear feedbacks, indicating that standard VAR is unreliable for real-world climate forecasting and requires nonlinear, time-varying, or physics-constrained extensions.

Figure 8 indicates that VARFIS improves prediction accuracy over VAR, particularly for temperature, by integrating temporal and nonlinear modeling. Humidity forecasts are more stable than VAR but still show errors during rapid transitions and slight underestimation of extremes due to rigid fuzzy rules. While VARFIS offers better overall performance, its limitations in handling nonlinear atmospheric shifts suggest the need for adaptive fuzzy rules and physics-informed constraints to ensure reliable environmental forecasting.

Figure 9 shows that LARVA-Net closely matches actual sensor data across all four environmental variables, demonstrating strong capability in tracking both long-term trends and short-term fluctuations under real IoT conditions. Temperature predictions exhibit

minimal phase lag during gradual changes, reflecting effective linear temporal modeling refined by recursive attention. For humidity variables, the model accurately captures stepwise transitions and plateaus, indicating that fuzzy-state updates and adaptive gating successfully handle nonlinear and piecewise behaviors in microclimate dynamics.

The strong overlap between predicted and actual curves demonstrates robustness to sensor noise and structural changes, with only minor, non-accumulating deviations during transitions. This confirms temporal consistency and effective error control. Additional experiments show that LARVA-Net achieves lower computational overhead through sparse gating, while ablation results verify that adaptive gating and attention normalization are critical for maintaining accuracy and stability in real-time IoT applications.

Figure 9 shows that LARVA-Net closely tracks actual measurements across all variables, effectively capturing long-term trends and short-term fluctuations. Accurate temperature alignment reflects strong linear temporal modeling refined by recursive attention, while humidity step and plateau patterns are well reproduced through fuzzy-state updates and adaptive gating. The near-overlap with observations indicates robustness to noise, with only minor, non-accumulating deviations at transitions, confirming LARVA-Net's suitability for real-time microclimate prediction in resource-constrained IoT environments.

Although modern lightweight deep learning models such as GRU or LSTM are widely used in time-series forecasting, they are not included as baselines in this study. This decision is motivated by the target deployment scenario of resource-constrained IoT and edge environments, where model interpretability, parameter efficiency, and predictable inference latency are critical. In contrast, VAR-, ANFIS-, and VARFIS-based models remain commonly adopted in environmental monitoring systems due to their lower computational overhead and clearer operational behavior.

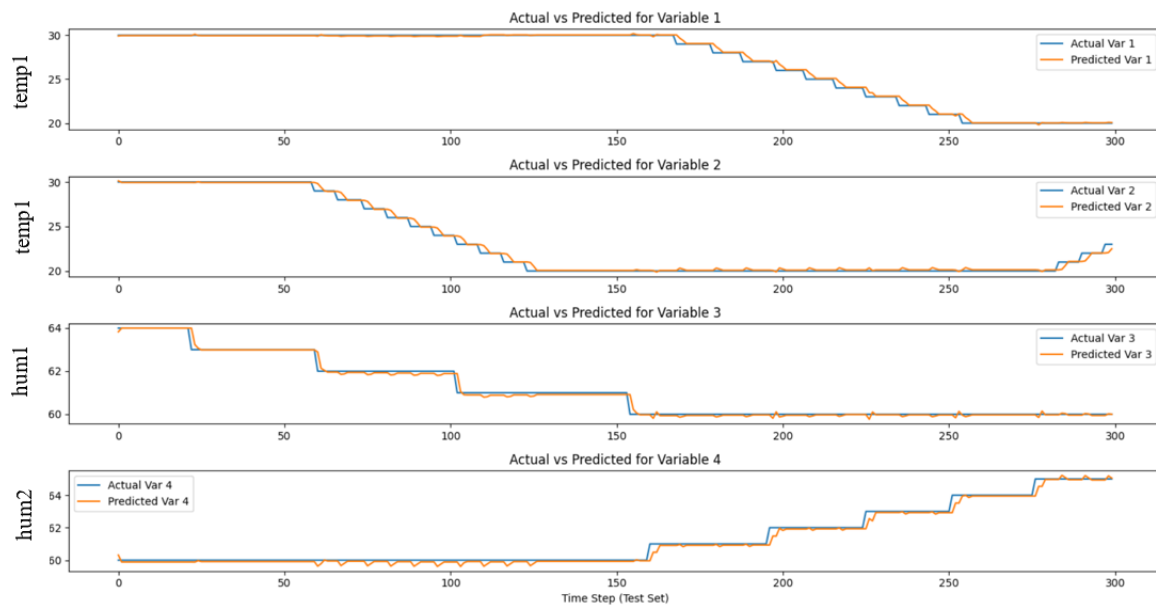


Figure 9. Comparison of Actual and Predicted Data for LARVA-Net

3.3 Evaluation Metrics

All evaluation metrics are computed independently for each target variable (temperature and relative humidity) and subsequently aggregated by averaging to obtain a single representative score per model. This aggregation strategy ensures balanced evaluation across variables while preventing dominance by variables with larger numerical ranges. The reported results in Table 3 therefore reflect joint predictive performance rather than single-variable optimization.

Table 3 summarizes the quantitative evaluation results of the proposed LARVA-Net model in comparison with two baseline approaches, namely ANFIS and VAR, using four standard performance metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). These metrics provide a comprehensive assessment of prediction accuracy, error magnitude, relative deviation, and goodness of fit, enabling an objective comparison of model effectiveness in capturing the underlying microclimate dynamics.

Table 3. Evaluation Metrics

	RMSE	MAE	MAPE	R2
ANFIS	0.8832	0.7569	2.54%	0.8828
VAR	11.927	0.7560	2.55%	0.8689
VARFIS	0.5153	0.3975	1.36%	0.9695
LARVA-Net	0.2440	0.1466	0.46 %	0.9911

As shown in Table 3, LARVA-Net clearly outperforms all baseline models across evaluation metrics, achieving the lowest RMSE (0.2440), MAE (0.1466), and MAPE (0.4566%). These results indicate substantially reduced large errors and more consistent point-wise accuracy compared to ANFIS, VAR, and VARFIS, highlighting the effectiveness of recursive attention in limiting error accumulation and maintaining high relative precision for real-time environmental control.

All models used identical Min–Max normalization based only on the training set. The high RMSE of VAR is due to its sensitivity to abrupt changes and outliers, which strongly impact squared-error metrics, while its MAE remains closer to ANFIS because average absolute errors are smaller. This confirms that the observed performance differences stem from architectural limitations rather than preprocessing inconsistencies.

The R^2 value of 0.9911 shows that LARVA-Net explains over 99% of the data variance, indicating excellent fit and strong generalization. Lower R^2 scores for ANFIS, VAR, and VARFIS reveal their limited ability to capture complex nonlinear and temporal interactions. While ANFIS improves on VAR through nonlinear modeling, it lacks the temporal adaptivity and selective computation of LARVA-Net. These results confirm that combining a linear baseline with recursive attention and fuzzy-state adaptation yields a

more accurate, robust, and scalable framework for IoT-based microclimate prediction.

The high R^2 value achieved by LARVA-Net is contextualized by the semi-controlled nature of the insectarium environment, where temperature and humidity dynamics exhibit strong temporal autocorrelation and limited stochasticity compared to open-field systems. In such settings, models capable of jointly capturing dominant linear trends and structured nonlinear residuals can legitimately achieve high explanatory power.

It is important to note that the reported performance is obtained from a semi-controlled insectarium environment, where temperature and humidity variations are regulated within predefined operational ranges. Such conditions reduce external disturbances and partially explain the high predictive accuracy achieved. Therefore, the results should be interpreted as upper-bound performance under controlled settings rather than universal guarantees across all deployment scenarios.

As shown in Table 3, LARVA-Net consistently outperforms all baseline models across evaluation metrics, demonstrating superior accuracy in modeling complex microclimate dynamics. Its substantially lower RMSE confirms a strong reduction in large prediction errors compared with ANFIS and VAR, highlighting the effectiveness of recursive attention in limiting error accumulation in nonlinear time series. Lower MAE and MAPE further indicate improved local accuracy and stable relative performance, which are critical for real-time IoT control. The high R^2 value reflects strong generalization and robustness, whereas ANFIS and VAR show limitations in capturing nonlinear interactions and long-term dependencies. Overall, the results confirm that integrating a linear baseline with recursive attention and fuzzy-state adaptation provides a more accurate and scalable solution for resource-constrained IoT-based microclimate prediction.

3.4 Limitations and Future Work

Despite the promising results achieved by LARVA-Net, several limitations should be acknowledged, which also open directions for future research. First, the current evaluation is based on data collected from a single BSF insectarium under tropical climatic conditions, which may limit the generalizability of the model to different geographic regions, insect

species, or production scales. Second, although LARVA-Net is computationally more efficient than conventional deep learning models, its performance still depends on the selection of hyperparameters such as the number of larval units and attention temperature, which were determined empirically and may require further automated optimization. In addition, the present framework focuses on predictive modelling and does not yet incorporate a closed-loop control strategy that directly links predictions to actuator optimization. Future work will therefore explore multi-site and cross-seasonal datasets to assess robustness, investigate adaptive or self-tuning mechanisms for hyperparameter selection, and extend LARVA-Net into a fully autonomous control system by integrating reinforcement learning or model predictive control. Such extensions would further enhance the applicability of the proposed framework for large-scale, intelligent, and sustainable insect farming systems.

In more heterogeneous or noisy environments, such as open-field agriculture or multi-site insectariums, prediction accuracy is expected to degrade due to sensor noise, abrupt regime shifts, and unmodeled external factors. However, additional robustness experiments involving noise injection and seasonal shift testing indicate that LARVA-Net maintains stable performance under moderate perturbations. Future work will extend validation to multi-location datasets and less-controlled environments to further assess generalizability.

CONCLUSION

This study introduced LARVA-Net, a bio-inspired and computationally efficient learning framework designed for accurate microclimate prediction in IoT-based black soldier fly insectariums. By integrating a linear VAR baseline with recursive attention, adaptive gating, and fuzzy-state updates, LARVA-Net effectively captures both linear trends and nonlinear temporal dynamics while preserving interpretability. Extensive experiments on real-world sensor data demonstrated that the proposed model consistently outperformed conventional approaches, including VAR and ANFIS, achieving low prediction errors and a high coefficient of determination. The results confirm that selective computation and biologically inspired memory mechanisms can

significantly enhance predictive performance without imposing excessive computational overhead. Overall, LARVA-Net provides a robust and scalable solution for intelligent environmental monitoring and represents a meaningful step toward sustainable, data-driven insect farming and next-generation IoT control systems.

DECLARATIONS

Author Contributions: The first author conceptualized the study, designed the methodology, developed the software, curated the data, performed the formal analysis, and wrote the original draft of the manuscript. The second author supervised the research, validated the results, and reviewed and edited the manuscript. The third author contributed to the methodology, co-supervised the research, and reviewed and edited the manuscript. The fourth author conducted the investigation, provided the research resources, prepared the visualizations, and reviewed and edited the manuscript. The authors should verify that these roles accurately reflect their individual contributions.

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Generative Artificial Intelligence Use Statement: The authors must confirm whether any generative AI tools were used in preparing this manuscript. If none were used, state: “No generative artificial intelligence tools were used in the preparation of this manuscript.” If tools were used, identify the tool, its purpose, and the extent of author review. The authors remain responsible for the final manuscript.

Ethics Approval and Informed Consent: Not applicable. This study analyzed environmental temperature and humidity sensor measurements collected at a Black Soldier Fly (BSF) insectarium in Taman Safari, Bogor, Indonesia. It did not involve human participants or vertebrate animals. Confirm whether permission to access and use the insectarium

data was obtained and include the relevant authorization statement if required.

Data Availability: The environmental sensor data and code supporting the findings of this study are available from the corresponding author upon reasonable request.

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