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PERFORMANCE EVALUATION OF ARFIMA–BPNN–RBF HYBRID MODEL USING NASA TEMPERATURE DATA IN MATARAM

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Abstract— *Climate change and increasingly dynamic air temperature fluctuations require accurate forecasting methods to support decision-making across various sectors, including agriculture, environmental management, and disaster mitigation. However, long-term temperature data generally exhibit complex characteristics involving linear patterns, nonlinear relationships, and long-term dependencies, making them difficult to model optimally using a single approach. Therefore, this study aims to analyze and evaluate the performance of the ARFIMA–BPNN–RBF hybrid model for long-term temperature forecasting in Mataram, West Nusa Tenggara Province (NTB), Indonesia, using monthly satellite-based temperature data (NASA) from 2015 to 2024. In this study, the ARFIMA model was employed to represent long-term memory patterns, the Backpropagation Neural Network (BPNN) was utilized to capture nonlinear relationships in the data, while the Radial Basis Function (RBF) model was applied to refine forecasting results. Model performance was evaluated using Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and accuracy metrics. The results on testing data showed that the ARFIMA, RBF, and BPNN models produced MAPE values of 1.94%, 6.38%, and 6.56%, respectively. Meanwhile, the ARFIMA–RBF hybrid model achieved a MAPE value of 1.97%, whereas the ARFIMA–BPNN–RBF hybrid model obtained the lowest MAPE value of 1.13% and a MAPE-based performance score of 98.86%. These results suggest that, for the dataset and single chronological train–test split evaluated in this study, the ARFIMA–BPNN–RBF hybrid model achieved lower forecasting errors than the individual and two-stage hybrid models considered.*

Keywords*: ARFIMA, BPNN, hybrid model, RBF, temperature forecasting.*

INTRODUCTION

Long-term temperature data is a crucial climate indicator in various sectors, such as agriculture, energy, health, and disaster mitigation [1]. Increasingly dynamic temperature patterns from year to year create an urgent need for more accurate predictions, particularly in the context of climate change adaptation and data-driven policy making [2]. Long-term temperature predictions can assist governments in designing natural resource management strategies, determining optimal planting times, and preparing for potential extreme weather events [3]. Therefore, the development of forecasting methods capable of capturing the dynamics of temperature data that are nonlinear, nonstationary, and have long-term memory effects is very important.

Various methods have been used to forecast time series data, ranging from classical statistical models such as ARIMA (AutoRegressive Integrated Moving Average), ARFIMA (Autoregressive Fractionally Integrated Moving Average), and ETS (Error, Trend, Seasonality) to artificial intelligence methods such as BPNN (Backpropagation Neural Network), RBF (Radial Basis Function), LSTM (Long Short-Term Memory), and modern hybrid forecasting. However, each method has its own advantages and disadvantages. Statistical models excel at capturing linear structures and memory



effects, but are less than optimal when dealing with nonlinear patterns [4]. Meanwhile, neural network methods are capable of learning nonlinear patterns well, but are often sensitive to noise and difficult to capture long-term dependencies [5]. Therefore, the use of a single method often does not produce optimal prediction accuracy, so a hybrid approach that combines the advantages of several methods is needed [6].

The ARFIMA model is known to be effective for handling data with long-memory and non-stationary characteristics [7]. The ARFIMA model has been widely applied to long-term time-series forecasting problems, particularly for data exhibiting persistence and temporal dependence [8]. A number of studies show that ARFIMA has better capabilities than ARIMA in capturing long-memory characteristics in time series [9]. According to [10], the conditional autoregressive fractionally integrated moving average (CARFIMA) model, which extends the ARFIMA framework, has been successfully applied to satellite land surface temperature data. The study demonstrated that long-memory models are capable of representing persistent spatial-temporal dependence and provide competitive predictive performance for temperature forecasting.

The BPNN model is a prediction model that can effectively learn nonlinear patterns through a process of repeated learning and has been widely applied in meteorological and climate-related forecasting because of its ability to approximate complex nonlinear relationships [11]. Recent studies on satellite-based environmental forecasting have demonstrated that BPNN performs effectively for predicting temperature and other atmospheric variables by learning nonlinear dependencies from historical observations. A recent study on NASA-based wind speed forecasting demonstrated that BPNN achieved good predictive performance for long-term environmental time-series prediction, producing an MSE of 0.007634 and a MAPE of 11.63%. Although the forecasting target differs from temperature, both variables originate from satellite-derived environmental time-series and exhibit nonlinear temporal dynamics, supporting the applicability of BPNN in environmental forecasting tasks [12].

The RBF model is a type of neural network with a simple architecture that excels in training speed and generalization capabilities for nonlinear patterns [13]. This method has been applied in various contexts, such as energy load forecasting, air quality modeling, financial prediction, and parameter estimation in dynamic systems. The results of the study [14] show that the error accuracy rate is better using the Radial Basis Function JST method with a network architecture of 12 inputs, 10 hidden layers, and 1 output and a spread value of 1.8 with an MSE calculation of 0.012 for palm oil export commodity data and 0.034 for coffee. The RMSE value of the palm oil export commodity data error obtained was 0.034 and coffee was 0.018 compared to the Backpropagation JST algorithm with a network architecture of 12-10-1 with a learning rate of 0.1 and an epoch of 1000, the MSE calculation for palm oil export commodity data error was 0.120 and for coffee it was 0.035. The RMSE value for palm oil export commodity data error was 0.346 and for coffee it was 0.189.

Although these three methods have been proven effective individually in various prediction contexts, research that directly combines ARFIMA, BPNN, and RBF in a single hybrid framework is still very limited [15]. The combination of these three methods has the potential to produce a more comprehensive model, as ARFIMA is capable of capturing long-term dynamics, while BPNN and RBF can learn complex nonlinear variations [16]. The lack of studies combining these three methods opens up new research opportunities to produce more accurate and stable hybrid models, especially for long-term temperature prediction [17].

The purpose of this study is to analyze and evaluate the performance of the ARFIMA–BPNN–RBF hybrid model in making long-term temperature predictions, with a focus on developing a model capable of integrating the ARFIMA's ability to capture long-memory patterns, the BPNN's ability to learn non-linear relationships, and the RBF's ability to smooth prediction results. This study also aims to measure the accuracy of the hybrid model's predictions using indicators such as MAPE, RMSE, and accuracy rate, and to compare it with the performance of single and partial hybrid models. Thus, this study is expected to demonstrate the effectiveness of hybrid models in producing more reliable temperature predictions, which can support strategic planning in various sectors such as agriculture, energy, and disaster mitigation.

MATERIALS AND METHODS

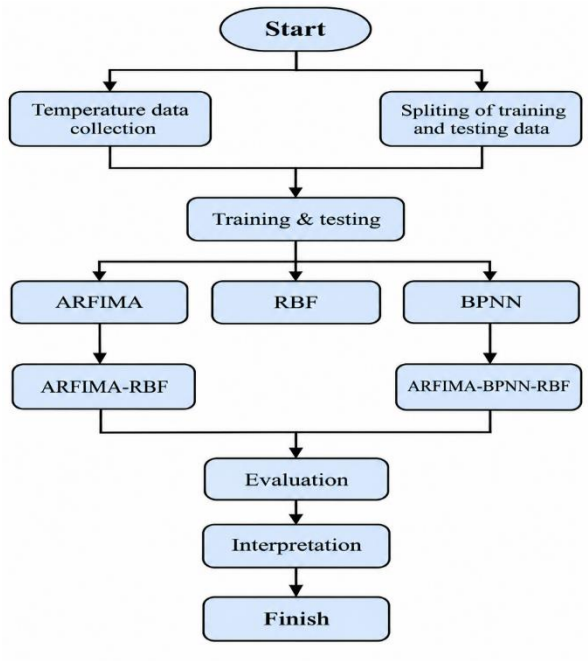
This study is an experimental quantitative study that aims to design, build, and implement a MATLAB-based Graphical User Interface (GUI) to simulate satellite (NASA) temperature data forecasting using the ARFIMA–BPNN–RBF hybrid model [18]. This GUI is designed to be interactive and easy to use, while allowing users to execute the entire modeling process, from training to comprehensive model evaluation [19]. The

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temperature dataset was divided chronologically into 80% training data and 20% testing data. The same chronological train–test partition was applied to the individual and hybrid models to ensure a consistent basis for performance comparison. The training observations were used for model development, whereas the testing observations were kept separate and used only for evaluating forecasting performance on unseen observations. The research also includes simulation experiments to test the performance of each individual method (ARFIMA, BPNN, RBF) and hybrid models on specific time series datasets, with evaluation using MSE (Mean Squared Error), RMSE (Root Mean Squared Error), and MAPE (Mean Absolute Percentage Error) indicators to assess prediction accuracy. This approach enables a systematic comparison of model performance and supports the development of effective and reliable long-term temperature prediction software.

This study uses temperature time series data, which is classified as interval-scaled quantitative data. Characteristically, temperature data has complex patterns, including nonlinearity, high fluctuations, long-term trends, and is influenced by various external factors such as climatic conditions, seasonal changes, and global and local meteorological phenomena. Temperature data also often exhibit autocorrelation, seasonal patterns, and indications of long-memory. The research data source was obtained via satellite over the last ten years on a monthly basis.



Source: (Research Results, 2025)

Figure 1. Research Procedure

Figure 1 illustrates the research procedure in the diagram, which depicts a structured workflow in developing a hybrid ARFIMA–BPNN–RBF model for temperature forecasting. The process begins with the collection of temperature data, which is then divided into training and testing data as the basis for model training. The next stage is the training and testing process on three basic models, namely ARFIMA, RBF, and BPNN. The ARFIMA model was specified using the parameter configuration (p = 1, d=0, q = 1), where p and q denote the autoregressive and moving-average orders, respectively, while d denotes the differencing parameter used in the ARIMA approximation adopted in this study. The BPNN model was constructed using a feedforward architecture with one hidden layer, where the number of neurons is determined through experimentation, and training is performed using the backpropagation algorithm. The RBF model consisted of a single hidden layer with radial basis activation functions, where the centers are determined using a clustering method and the output weights are estimated using least squares.

In this study, the ARFIMA component was implemented using an ARIMA approximation with the parameter configuration $((p = 1, d = 0, q = 1))$. The ARFIMA–BPNN–RBF terminology is retained throughout the manuscript to denote the proposed hybrid framework, while the statistical component itself is explicitly identified as an ARIMA approximation because the fractional differencing parameter was not estimated. The parameter configuration was selected based on visual inspection of the autocorrelation function (ACF) and empirical trial-and-error to obtain a stable forecasting component with a relatively low forecasting error among the evaluated configurations. Because (d=0), the implemented statistical component does not explicitly estimate fractional differencing and therefore should not be interpreted as a fully parameterized ARFIMA model. Instead, it serves as the statistical baseline component within the proposed ARFIMA–BPNN–RBF hybrid framework. The reconstructed baseline series was subsequently adjusted using a 12-month seasonal index to represent recurring monthly temperature variation.

The BPNN model employed a feedforward neural network architecture with two hidden layers consisting of 15 and 10 neurons, respectively. The hidden layers used the tansig activation function, while the output layer used the purelin activation function. The input data used a sliding-window approach with 12 input lags representing monthly observations from the previous year. The network training process utilized the resilient

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backpropagation (trainrp) algorithm with a maximum of 600 epochs. Training was stopped when the maximum number of epochs was reached or when validation performance failed to improve. The learning rate is implicitly handled by the resilient backpropagation (trainrp) algorithm. Data normalization was performed using min-max scaling in the interval ([-1,1]). The dataset was divided chronologically into 80% training data and 20% testing data. The same chronological partition was maintained across the evaluated models to ensure that model performance was compared using the same training and testing observations. Within the BPNN training process, parameter optimization was performed using the training observations, while the 20% testing observations were reserved for the final performance evaluation. No separate 10% validation subset was used in the experimental design reported in Table 3. The RBF model used a single hidden layer with Gaussian radial basis activation functions. The model was trained using the MATLAB newrb() function with a spread parameter of 1.0 and a maximum of 50 neurons. The input structure also used 12 input lags through a sliding-window mechanism. The center-selection process in the RBF network was performed automatically during the incremental training process provided by the MATLAB implementation, while the output weights were estimated using least-squares optimization.

The proposed ARFIMA–BPNN–RBF hybrid model follows a sequential residual-correction architecture with additive integration. First, the ARFIMA component is used to generate the baseline forecast, denoted by $(\widehat{y_t^{ARFIMA}})$, which represents the linear temporal structure of the temperature series. Second, the residual series is calculated as the difference between the observed temperature and the ARFIMA baseline forecast. The BPNN is then trained on this residual series to estimate the nonlinear component that is not captured by the baseline model. In parallel, the RBF network is applied to the ARFIMA baseline output to generate a refinement term rather than an independent complete forecast. Specifically, the RBF output is treated as a correction component, denoted by (Δ_t^{RBF}), which adjusts the ARFIMA baseline forecast. Finally, the three components are combined additively to obtain the final hybrid forecast. Thus, the RBF component does not replace the ARFIMA forecast or represent an additional complete temperature forecast; instead, it provides a refinement to the baseline forecast, while the BPNN provides a nonlinear residual correction. This formulation is intended to integrate the temporal structure represented by the statistical component with nonlinear information learned by the neural-network components. The mathematical formulation of the proposed hybrid model is presented in Equations (1)–(5).

$$\widehat{y_t^{ARFIMA}} = f_{ARFIMA}(y_t) \quad (1)$$

$$e_t = y_t - \widehat{y_t^{ARFIMA}} \quad (2)$$

$$\Delta_t^{RBF} = f_{RBF}\left(\widehat{y_t^{ARFIMA}}\right) \quad (3)$$

$$\widehat{e_t^{BPNN}} = f_{BPNN}(e_t) \quad (4)$$

$$\widehat{y_t^{Hybrid}} = \widehat{y_t^{ARFIMA}} + \Delta_t^{RBF} + \widehat{e_t^{BPNN}} \quad (5)$$

Where (Δ_t^{RBF}) represents the RBF-based refinement term and is not interpreted as an independent complete forecast. The final hybrid prediction is therefore obtained by adding the ARFIMA baseline forecast, the RBF refinement term, and the BPNN-estimated residual component.

RESULTS AND DISCUSSION

Result

In time series modeling and forecasting, various approaches are used to capture complex data patterns. In this study, three different models were used.

ARFIMA Model

The ARFIMA component in the proposed framework was implemented through an ARIMA approximation with the configuration $((p = 1, d = 0, q = 1))$. Therefore, the results presented for this component represent the performance of the ARIMA-approximated statistical baseline rather than a fully estimated fractional ARFIMA model [10]. The general ARFIMA formulation is presented in Equations (6)–(8) to describe the theoretical basis of the statistical component, whereas the actual implementation used in this study fixed the differencing parameter at (d=0). Consequently, fractional differencing and its associated long-memory parameter were not estimated from the observed temperature series.

$$(1 - \phi^1 B - \phi^2 B^2 - \cdots - \phi_{\mathrm{p}} B^{\mathrm{p}})(1 - B)^{\mathrm{d}} X_{\mathrm{t}} = \left(1 + \theta^1 B + \theta^2 B^2 + \cdots + \theta_q B^q\right)\varepsilon_{\mathrm{t}} \quad (6)$$

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Description:
X_t = temperature value in month/year t
B = backshift operator $BX_t = X_{t-1}$
p = order of autoregression (AR)
d = order of fractional differencing
q = order of moving average (MA)
ϕ_i= AR coefficient
θ_j= MA coefficient
ε_t = error (white noise)

The operator $(1-B)^d$ is expanded as:

$$(1-B)^d = \sum_{k=0}^{\infty} \binom{d}{k} (-B)^k \quad (7)$$

With:

$$\binom{d}{k} = \frac{\Gamma(d+1)}{\Gamma(k+1)\,\Gamma(d-k+1)} \quad (8)$$

Equations (6)–(8) describe the theoretical ARFIMA formulation, including the fractional differencing operator. However, because the implemented configuration used (d=0), the fractional differencing component was not estimated in the present study. Accordingly, the statistical component was used as an ARIMA approximation within the proposed ARFIMA–BPNN–RBF framework, and the results should be interpreted based on this implementation rather than as empirical evidence of statistically verified long-memory behavior.

BPNN Model

BPNN is a type of multilayer neural network (MLP) that uses the backpropagation algorithm for training. This model is used to map complex relationships between inputs and outputs with the ability to handle nonlinearities [20]. The mathematical model of BPNN is in accordance with equations (9), (10), (11), and (12).
Output neuron:

$$y_j = f\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right) \quad (9)$$

Description:
y_j= output of neuron j
x_i= input of neuron i
w_{ij}= weight from neuron i to neuron j
b_j= bias of neuron j
$f(\cdot)$= activation function.
Error function (Loss Function)

$$\text{MSE} = \frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2 \quad (10)$$

Description:
y_t= the actual temperature at time t
$\hat{y}_t$= temperature predicted by BPNN
N= amount of data
Update weight (Backpropagation)

$$w_{ij}^{\text{new}} = w_{ij}^{\text{old}} - \eta \frac{\partial E}{\partial w_{ij}} \quad (11)$$

$$b_j^{\text{new}} = b_j^{\text{old}} - \eta \frac{\partial E}{\partial b_j} \quad (12)$$

Where η is the learning rate and E is the error function value (MSE).

RBF Model

RBF is a type of artificial neural network that uses radial basis functions as activation functions in the hidden layer [21]. This model projects inputs into a high-dimensional space, allowing for clearer separation of nonlinear patterns, with each neuron in the hidden layer having a specific center and width that determines its response to inputs. The mathematical model of RBF is as shown in equations (13) and (14).
Network output:

$$y(\boldsymbol{x}) = \sum_{i=1}^{N} w_i \ \rho(||\boldsymbol{x} - c_i||) \quad (13)$$

Description:
$y(\boldsymbol{x})$= network output or temperature prediction
$\boldsymbol{x}$= input vector
N= number of neurons in the hidden layer
c_i= center of the i -th neuron
w_i= output weight for the i - th neuron
$\rho(\cdot)$= radial basis function, usually Gaussian $\rho(r) = \exp(-\gamma r^2)$
γ= width or spread parameter of the Gaussian function

In this study, forecasting performance was evaluated using MSE, RMSE, and MAPE. For descriptive comparison, a MAPE-based performance score was also calculated using the following transformation:

$$Performance\ score(\%) = (1 - \text{MAPE}) \times 100 \quad (14)$$

Where MAPE is expressed in decimal form. The interpretation of MAPE values adopted in this study is based on forecasting error categories reported in previous forecasting literature and is presented in Table 1.

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Table 1. Interpretation of Forecasting Performance Categories Based on MAPE

Percentage	Decimal	Forecasting Performance
>50%	>0.50	Poor
20–50%	0.20–0.50	Reasonable
10–20%	0.10–0.20	Good
<10%	<0.10	Excellent

Source: (Research Results, 2025)

Table 1 presents the interpretation of MAPE values used to evaluate forecasting performance. The Poor category is assigned when MAPE is greater than 50%, indicating that prediction errors are very high and the model is unable to represent the observed data patterns adequately. MAPE values between 20% and 50% indicate Reasonable forecasting performance, suggesting that the model still produces considerable deviations from the observed values. Values between 10% and 20% indicate Good forecasting performance, meaning that prediction errors remain within an acceptable range for many practical applications. Meanwhile, MAPE values below 10% indicate Excellent forecasting performance, suggesting that the predicted values are very close to the observed values and that the model exhibits a low level of forecasting error [22].

The data used in this study is monthly temperature data for the period 2015–2024, with a total of 120 observations representing long-term temperature conditions. The data is presented in tabular form to provide an initial overview of general patterns, value ranges, and temperature fluctuations between months and years before analysis and modeling are performed. The monthly data used in this study are presented in Table 2.

Tabel 2. Monthly Historical Temperature Data From 2015–2024 Used in the Study

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2015	26.37	26.33	26.81	26.80	26.08	25.89	25.94	26.34	27.53	28.71	29.85	28.03
2016	28.34	27.05	28.08	27.75	27.55	26.98	26.26	26.54	28.24	28.32	28.45	26.74
2017	26.32	26.34	26.89	26.92	26.47	25.61	25.70	26.44	27.89	28.38	27.74	26.98
2018	26.20	26.37	26.90	27.26	26.55	26.48	26.26	26.47	27.86	28.69	28.68	27.14
2019	26.67	26.98	26.80	27.13	26.43	25.78	25.78	26.29	27.28	28.95	29.47	29.38
2020	27.80	27.28	27.33	27.42	27.09	26.77	26.42	27.02	28.63	28.36	28.96	26.93
2021	26.49	26.18	26.51	26.52	26.70	26.93	26.55	27.46	27.80	28.34	27.58	27.16
2022	26.33	26.29	27.01	27.29	27.29	26.44	25.83	26.98	28.05	27.57	27.24	27.36
2023	26.71	26.00	26.85	26.68	26.16	26.46	26.39	26.91	27.96	28.89	29.78	28.84
2024	28.02	27.85	26.66	27.62	27.52	27.09	26.68	27.64	29.03	29.65	28.86	27.33

Source: (Research Results, 2025)

Table 2 shows that the monthly temperature data from 2015–2024 exhibit noticeable seasonal fluctuations. Higher temperatures generally occur during September–November, with several observations exceeding 29°C, whereas lower temperatures are commonly observed during June–August, with values around 25–26°C. These recurring patterns indicate the presence of seasonal variation and temporal dependence in the temperature series.

The repeated increase in temperature during September–November and the relatively lower temperatures during June–August suggest that the dataset contains a consistent seasonal structure. Such characteristics support the application of hybrid forecasting models, where the linear component represents the overall temporal structure while the neural-network components are intended to model nonlinear variations that may not be adequately represented by the linear model alone. The training and testing data results are shown in Table 3.

Table 3. Performance Comparison of Forecasting Models on the 80% Training and 20% Testing Datasets.

Algorithm	MSE	RMSE	MAPE (%)	MAPE-Based Performance Score (%)
Training (80%) data				
ARFIMA	0.34	0.59	1.92	98.07
RBF	0.17	0.41	1.37	98.62
BPNN	0.25	0.50	1.64	98.35
ARFIMA-RBF	0.53	0.72	2.04	97.95
ARFIMA-BPNN-RBF	0.26	0.51	1.15	98.84
Testing (20%) data				
ARFIMA	0.48	0.69	1.94	98.05
RBF	3.76	1.94	6.38	93.61
BPNN	4.61	2.14	6.56	93.43
ARFIMA-RBF	0.43	0.66	1.97	98.02
ARFIMA-BPNN-RBF	0.15	0.39	1.13	98.86

Source: (Research Results, 2025)

Table 3 shows that the evaluation results on the training data (80%) indicate that the ARFIMA-BPNN-RBF model achieved the best performance among the evaluated models. Although the dataset consisted of only 120 monthly observations, hybrid

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neural-based models were included to evaluate whether nonlinear learning components could improve forecasting performance over conventional statistical and simpler hybrid approaches. Model complexity was therefore explored comparatively rather than assumed to be optimal a priori. The performance comparison also indicates that increasing model complexity did not automatically improve forecasting performance, as different hybrid configurations produced different levels of prediction error, with the ARFIMA–RBF model yielding the highest MAPE (2.04%) and the lowest MAPE-based performance score (97.95%) during training.

Suggesting that additional complexity may not be beneficial for relatively limited data. Conversely, the ARFIMA-BPNN-RBF model achieved the best performance, with the lowest MAPE (1.15%) and the highest MAPE-based performance score (98.84%), indicating that its hybrid architecture was able to capture the data pattern effectively without clear evidence of performance degradation based on the reported error metrics. These findings suggest that model effectiveness in this study was influenced more by the suitability of the architecture to the data characteristics than by model complexity alone. The noticeably higher testing errors observed for the single RBF and BPNN models compared with their corresponding training errors may indicate reduced generalization capability or possible overfitting. However, this interpretation remains tentative because no additional diagnostic analyses, such as learning-curve evaluation, validation-loss monitoring, residual analysis, rolling-origin validation, or parameter sensitivity analysis, were performed.

Moreover, although the relatively small sample size (120 monthly observations) compared with the complexity of the neural-network architectures may have contributed to the observed performance gap, no formal parameter-to-sample ratio analysis was conducted. Therefore, the observed differences between training and testing performance should be interpreted cautiously and should not be considered conclusive evidence of overfitting. Furthermore, model evaluation was conducted using a single chronological 80:20 train–test split to preserve the temporal order of the time-series data. Consequently, the reported forecasting performance reflects the results obtained under one validation scenario only and should therefore be interpreted with caution. More comprehensive validation strategies, such as rolling-origin evaluation, time-series cross-validation, robustness testing, and sensitivity analysis, were beyond the scope of this study but are recommended for future work to provide stronger evidence of model generalization and stability.

The evaluation results on the testing dataset (20%) indicate that the ARFIMA-BPNN-RBF model achieved the lowest MAPE (1.13%) and the highest MAPE-based performance score (98.86%) among the compared models, suggesting the best predictive performance based on the selected error metrics. This pattern is consistent with the training results, suggesting that the proposed hybrid model generalized better than the comparison models within the testing dataset used in this study. The ARFIMA and ARFIMA-RBF models also demonstrated stable performance, with MAPE values of approximately 1.95% and MAPE-based performance scores of approximately 98%, suggesting acceptable generalization ability.

However, it should be noted that the comparison in this study is based solely on deterministic error metrics (MSE, RMSE, and MAPE); therefore, the observed performance differences should be interpreted descriptively, as no statistical significance testing or uncertainty quantification was conducted. In contrast, the standalone RBF and BPNN models exhibited substantially higher MAPE values (above 6%), with corresponding MAPE-based performance scores decreasing to approximately 93%, indicating weaker generalization performance on the testing dataset. Furthermore, because model validation was limited to a single chronological 80:20 train-test split, additional validation procedures such as rolling-origin evaluation, time-series cross-validation, robustness testing, and sensitivity analysis are needed to provide stronger evidence regarding the stability and generalizability of the proposed hybrid model.

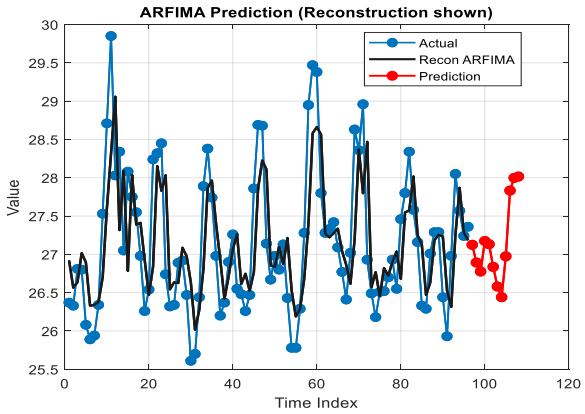
The simulation results suggest that the ARFIMA–BPNN–RBF model exhibited the most consistent forecasting performance across both the training and testing datasets based on the reported MAPE-based performance scores. The relatively small difference between training and testing errors indicates that the proposed hybrid architecture maintained more stable predictive behavior under the experimental conditions of this study than the comparison models. In contrast, the substantially larger increase in testing errors observed for the standalone RBF and BPNN models suggests that minimizing training error alone was insufficient to ensure good predictive performance on unseen data. Although these observations may indicate differences in model generalization, they should be interpreted descriptively because no statistical

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significance testing or additional robustness analyses were performed.

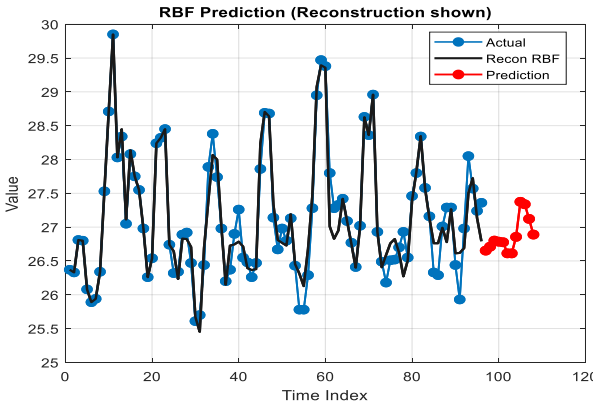
Actual data and prediction approach in the training process

During the training process, the model iteratively adjusts parameters so that the prediction results are closer to the actual data. The proximity between the actual data and the predicted data is measured using error MSE, RMSE, MAPE, and the MAPE-based Performance Score. The smaller the error value, the better the model is at approximating or representing the patterns found in the actual data [23].



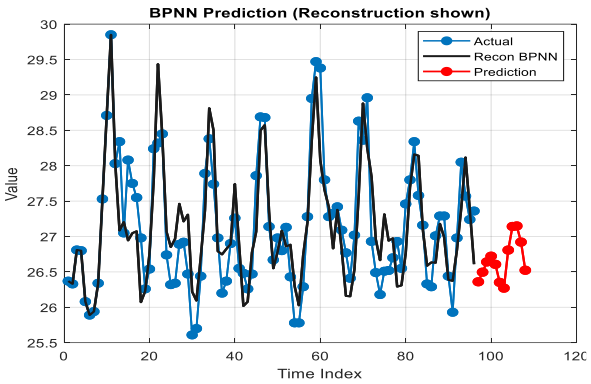
Source: (Research Results, 2025)

Figure 2. Comparison of observed and ARIMA-Approximated ARFIMA Predicted Temperature Values on the Training Dataset (80%), Illustrating the model's Ability to Capture the Linear Temporal Structure Used as the Baseline Component of the Proposed Hybrid Framework.



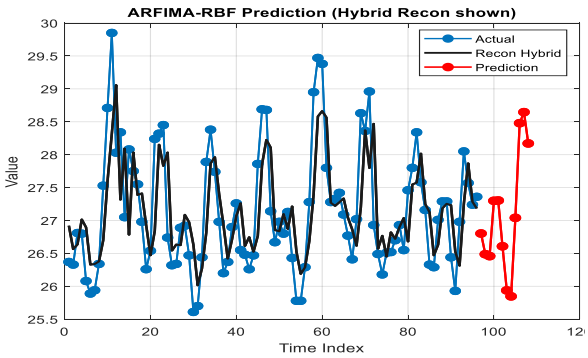
Source: (Research Results, 2025)

Figure 3. Comparison of Observed and Predicted Temperature Values Produced by the RBF Model on the Training Dataset (80%), Illustrating the Model's Capability to Learn Nonlinear Relationships in the Temperature Time Series.



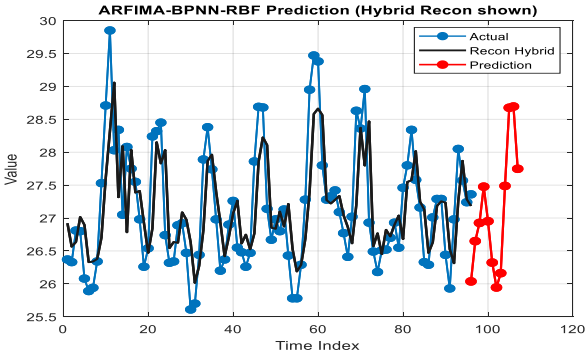
Source: (Research Results, 2025)

Figure 4. Comparison of Observed and Predicted Temperature Values Produced by the BPNN Model on the Training Dataset (80%), Demonstrating the Nonlinear Learning Performance of the Feedforward Neural Network.



Source: (Research Results, 2025)

Figure 5. Comparison of observed and predicted temperature values generated by the ARFIMA–RBF hybrid model on the training dataset (80%), illustrating the integration of linear baseline forecasting and nonlinear refinement.



Source: (Apriliya, 2025)

Figure 6. Comparison of Observed and Predicted Temperature Values Generated by the Proposed ARFIMA–BPNN–RBF Hybrid Model on the Training Dataset (80%), Demonstrating the Combined Contribution of the Linear Baseline, Nonlinear Refinement, and Residual Learning Components.

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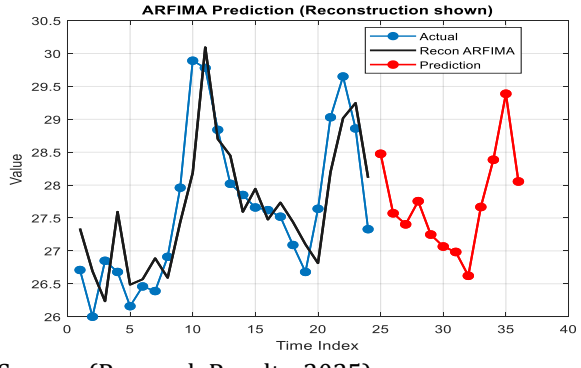
VOL. 12. NO. 2 NOVEMBER 2026
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The results of running on the training data show that each model has a different error rate. The RBF model has the lowest MSE (0.17) and RMSE (0.4183) among all single algorithms, followed by BPNN with MSE 0.25 and RMSE 0.50. ARFIMA showed a slightly higher error with an MSE of 0.34 and an RMSE of 0.59. Meanwhile, ARFIMA-RBF actually produced the largest error in the training stage, with an MSE of 0.53 and an RMSE of 0.72. The ARFIMA-BPNN-RBF hybrid model recorded an MSE of 0.26 and an RMSE of 0.51. As illustrated in Figures 2–6, the predicted temperature values generally followed the observed temporal patterns, although noticeable differences in the degree of agreement were observed among the models.

The ARFIMA–BPNN–RBF hybrid exhibited the closest visual agreement with the observed data, indicating that the integration of linear forecasting, nonlinear refinement, and residual learning enabled the model to represent both the overall trend and short-term fluctuations more effectively than the individual models. These findings indicate that the proposed ARFIMA–BPNN–RBF hybrid model provided more reliable forecasting performance during the training stage than the individual forecasting models.

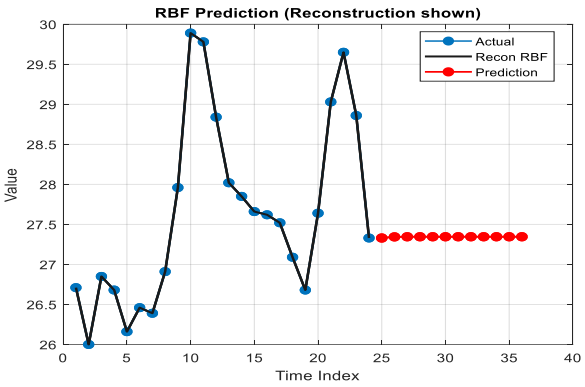
Actual data and prediction approach in the testing process

During the testing process, the model is tested using 20% of the data that was not involved in the training process. This stage aims to measure the model's ability to generalize new data. The forecasting performance was evaluated using MSE, RMSE, MAPE, and the MAPE-based performance score. [24].



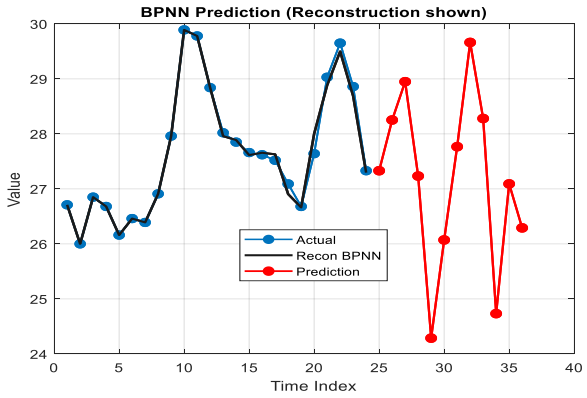
Source: (Research Results, 2025)

Figure 7. Comparison of Observed and ARIMA-Approximated ARFIMA Predicted Temperature Values on the Testing Dataset (20%), Illustrating the Baseline Forecasting Performance on Unseen Data.



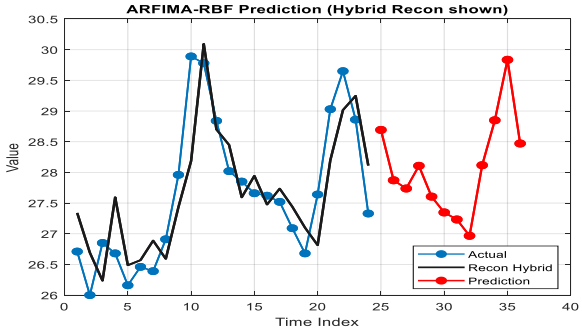
Source: (Research Results, 2025)

Figure 8. Comparison of Observed and Predicted Temperature Values Produced by the RBF Model on the Testing Dataset (20%), Illustrating the Model's Nonlinear Forecasting Performance.



Source: (Research Results, 2025)

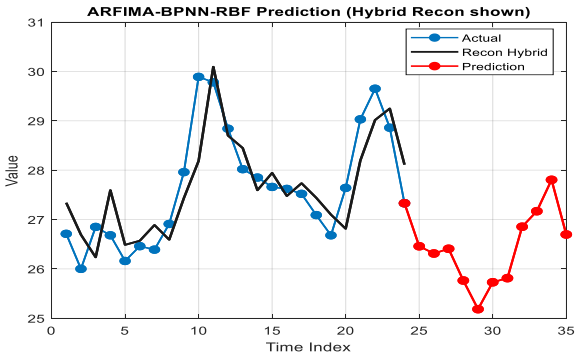
Figure 9. Comparison of Observed and Predicted Temperature Values Produced by the BPNN Model on the Testing Dataset (20%), Demonstrating the Generalization Performance of the Feedforward Neural Network.



Source: (Research Results, 2025)

Figure 10. Comparison of Observed and Predicted Temperature Values Generated by the ARFIMA–RBF Hybrid Model on the Testing Dataset (20%), Illustrating the Effectiveness of Combining Linear and nonlinear forecasting components.

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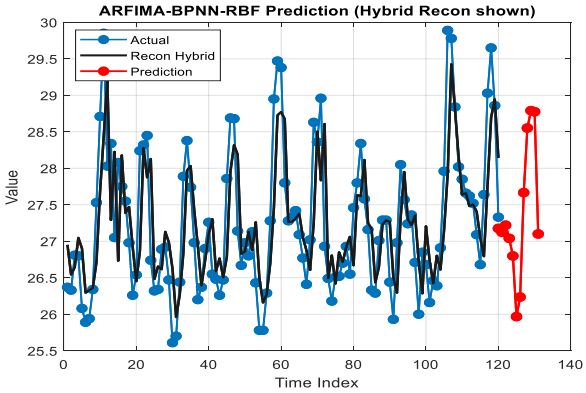


Source: (Research Results, 2025)

Figure 11. Comparison of Observed and Predicted Temperature Values Generated by the Proposed ARFIMA–BPNN–RBF Hybrid Model on the Testing Dataset (20%), demonstrating its Forecasting Performance on Unseen Observations.

The ARFIMA model was included in this study because it is designed to represent persistent temporal dependence through fractional differencing and has been widely applied in long-term time-series forecasting. In this study, the selection of the ARFIMA component was primarily motivated by the observed persistence in the autocorrelation pattern and by comparative evaluation with the other forecasting models. However, formal long-memory diagnostic tests, such as Hurst exponent estimation or Geweke–Porter–Hudak (GPH) testing, were not performed. Therefore, the presence of long-memory characteristics in the temperature series cannot be conclusively established, and the use of the ARFIMA component should be interpreted as a modeling choice rather than as confirmation of statistically verified long-memory behavior.

The model performance was evaluated using the testing dataset. Based on the reported error metrics, the ARFIMA model achieved an MSE of 0.48 and an RMSE of 0.69, while the ARFIMA–RBF model obtained an MSE of 0.43 and an RMSE of 0.66. In contrast, the single RBF and BPNN models produced higher error values, with MSE values of 3.76 and 4.61 and RMSE values of 1.94 and 2.14, respectively. Among the evaluated models, the ARFIMA–BPNN–RBF hybrid model achieved the lowest error metrics, with an MSE of 0.15 and an RMSE of 0.39. As illustrated in Figures 7–11, the predicted values generated by the proposed hybrid model closely followed the observed temperature series, with only minor deviations at several time points. In contrast, the standalone RBF and BPNN models exhibited larger deviations between the predicted and observed values, particularly during periods of greater temperature fluctuation, indicating weaker generalization performance on the testing dataset. The visual comparison presented in Figures 7–11 is generally consistent with the quantitative evaluation results shown in Table 3, where the ARFIMA–BPNN–RBF model exhibited the closest agreement between predicted and observed temperature values. However, these findings should be interpreted descriptively because no statistical significance testing or uncertainty analysis was performed. Accordingly, the reported results should be interpreted as comparative forecasting performance within the experimental setting of this study rather than as evidence confirming the presence of statistically verified long-memory characteristics. Model-Generated Temperature Forecasts for 2025



Source: (Research Results, 2025)

Figure 12. Model-Generated Monthly Temperature Forecasts for 2025 Produced by the Proposed ARFIMA–BPNN–RBF Hybrid Model Using Historical NASA Temperature Observations From 2015–2024. The 2025 Values Represent out-of-sample Forecasts Generated from Information Available Through 2024 and were not Evaluated Against Observed 2025 Temperature Data in this Study.

The proposed ARFIMA–BPNN–RBF hybrid model was subsequently used to generate monthly temperature forecasts for 2025 based exclusively on the historical NASA temperature observations available for 2015–2024. Because the 2025 observations were not included in the dataset used for model evaluation, these forecasts are presented as out-of-sample model-generated estimates rather than as validated observations. The predicted values range from 25.97°C to 29.42°C, with relatively higher values occurring during September–November. This pattern is consistent with the recurring seasonal variation identified in the historical data. The forecast series also shows a relatively smooth monthly transition, without extreme fluctuations outside the historical range. Nevertheless, the plausibility of these forecasts does

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not establish their predictive accuracy because no comparison with observed 2025 temperature data was conducted in this study.

The forecasting performance of the evaluated models was also examined using the complete historical dataset covering 2015–2024, consisting of both training and testing observations. The reported MSE and RMSE values represent descriptive error measures calculated from model predictions against the corresponding observed temperature values within the 2015–2024 dataset and do not represent forecasting errors for the 2025 projections. The ARFIMA model produced an MSE of 0.83 and an RMSE of 0.91, while the RBF model achieved an MSE of 1.07 and an RMSE of 1.03. The BPNN model produced the highest error among the evaluated models, with an MSE of 1.3845 and an RMSE of 1.17.

The ARFIMA–RBF hybrid model achieved an MSE of 0.51 and an RMSE of 0.72, whereas the proposed ARFIMA–BPNN–RBF hybrid model obtained the lowest MSE of 0.42 and RMSE of 0.64. These results indicate that, based on the complete 2015–2024 dataset, the proposed ARFIMA–BPNN–RBF hybrid model produced the lowest MSE and RMSE among the evaluated model configurations. The hybrid configuration combines the linear temporal component, nonlinear residual learning, and forecast refinement provided by the ARFIMA, BPNN, and RBF components, respectively.

Discussion

The following are the results of monthly temperature forecasts for 2025. This data provides an overview of temperature variations throughout the year, which can be used as a reference in understanding seasonal patterns and supporting planning processes in various sectors, such as agriculture, water resource management, and hydrometeorological disaster mitigation [25]. The predictions presented are based on the classification of monthly temperature values into four categories: cold (<20°C), cool (20–24°C), warm (25–28°C), and hot (>28°C) [26]. These categories are used to facilitate the interpretation of forecasted temperature patterns generated by the model. The forecast results can be seen in Table 4.

Table 4. Model-Generated Monthly Temperature Forecasts for 2025 Based on NASA Temperature Observations from 2015–2024.

Month	Temperature Prediction	Category
Jan	26.92	Warm
Feb	26.68	Warm
Mar	27.09	Warm
Apr	27.35	Warm
May	26.77	Warm
Jun	25.97	Warm
Jul	26.29	Warm
Aug	27.35	Warm
Sep	29.03	Hot
Oct	29.42	Hot
Nov	28.79	Hot
Dec	27.15	Warm

Source: (Research Results, 2025)

Table 4 presents the model-generated monthly temperature forecasts for 2025 obtained from the proposed ARFIMA–BPNN–RBF hybrid model using historical observations from 2015–2024. Most months are categorized as "Warm," while September, October, and November are classified as "Hot" based on the temperature classification adopted in this study. The relatively higher predicted temperatures during September–November are consistent with the recurring seasonal pattern observed in the historical dataset, in which temperatures generally increase during these months. This indicates that the proposed model preserved the dominant seasonal structure observed in the historical series. However, because the model was trained using observations through 2024 and no observed 2025 data were incorporated into the evaluation, these values should be interpreted as model-generated out-of-sample forecasts rather than validated predictions of actual 2025 temperatures. Therefore, the 2025 forecasts provide an illustration of the model's forecasting behavior under the available data conditions but do not constitute evidence of predictive accuracy for the realized 2025 temperature observations.

The results of this study show that the ARFIMA–BPNN–RBF hybrid model produced lower forecasting errors than the single ARFIMA model reported by [27] based on the evaluation metrics considered. Study [27] reported an MSE value of 1.48, whereas the hybrid model in this study obtained an MSE value of 0.42. This difference suggests that the integration of ARFIMA, BPNN, and RBF may provide a better representation of both linear and nonlinear patterns in temperature data. However, the comparison should be interpreted descriptively because no statistical significance testing or uncertainty analysis was conducted. Therefore, the observed performance difference cannot be considered statistically significant within the scope of this study. Nevertheless, the lower error metrics obtained by the hybrid model suggest its potential usefulness for long-term temperature forecasting applications.

Research conducted by [28] reported RMSE values ranging from 2.50 to 3.71 for the RBF model. In comparison, the ARFIMA–BPNN–RBF model developed in this study achieved an RMSE value of 0.64. Based on this metric comparison, the hybrid

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model produced lower forecasting errors than the RBF model reported in [28]. This difference suggests that combining ARFIMA, BPNN, and RBF may provide advantages in representing both linear and nonlinear characteristics of temperature time series data. However, the comparison should be interpreted descriptively because the studies were conducted using different datasets and no statistical significance testing was performed.

CONCLUSION

The results indicate that the proposed ARFIMA–BPNN–RBF hybrid forecasting model achieved the best overall predictive performance among the evaluated models based on the reported MSE, RMSE, MAPE, and MAPE-based performance score. Under the experimental conditions of this study and the single chronological 80:20 train–test split, the model consistently produced lower forecasting errors on both the training and testing datasets. These findings indicate that the proposed hybrid architecture provided the most favorable predictive performance among the evaluated configurations for the available dataset. Nevertheless, the results should not be interpreted as evidence of universal model superiority because the evaluation was based on one dataset and one chronological train–test split without statistical significance testing, uncertainty quantification, or rolling-origin validation.

The model-generated temperature forecasts for 2025 indicate predominantly warm conditions during the early to mid-year period, followed by relatively hotter conditions toward the end of the year, particularly during September–November. These projected patterns illustrate the model's ability to generate future monthly estimates based on the historical temperature structure observed during 2015–2024. However, because observed 2025 temperature data were not included in the evaluation, these forecasts should not be interpreted as evidence of validated predictive accuracy. Their practical applicability for climate-related planning therefore requires further evaluation against observed data and additional forecasting scenarios.

The findings suggest that the hybrid modeling approach may provide advantages for representing the characteristics of the temperature dataset analyzed in this study. However, further validation using data from different regions, time periods, and climatic conditions is needed to assess the broader applicability and robustness of the proposed model.

For future research, additional climatological variables, such as humidity, rainfall, and solar radiation, could be incorporated to improve forecasting performance. The use of more advanced neural network architectures, including LSTM and GRU, may also be explored to better capture temporal dependencies and nonlinear relationships. Furthermore, the development of automatic parameter optimization, multi-region analyses, and interactive visualization tools could enhance the usability and evaluation of forecasting models. The proposed approach may also provide useful information to support climate-related monitoring and planning activities.

DECLARATION OF AI USE

The authors declares that DeepL was used as an AI-assisted translation tool during the preparation of this manuscript to translate text between Indonesian and English. The author reviewed and revised the translated content to ensure its accuracy and appropriateness. The author remains fully responsible for the accuracy, originality, and final content of the manuscript.

AUTHOR CONTRIBUTIONS

Author	Contribution Roles
Delista Apriliya	Conceptualization, Methodology, Formal Analysis, Investigation, Data Curation, Software, Visualization, Writing – Original Draft.
Syaharuddin	Supervision, Validation, Project Administration, Review & Editing.
Vera Mandailina	Supervision, Validation, Review & Editing.
Saba Mehmood	Validation, Review & Editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare that there are no actual or potential conflicts of interest related to the research, writing, or publication of this article.

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