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A comparative study of hybrid GARCH–HOLT–BPNN models for rainfall forecasting using a MATLAB-based intelligent computing system

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Abstract

Rainfall forecasting is essential for water resource management, hydrometeorological disaster mitigation, and agricultural planning. This study addressed the limitations of previous research that focused on single models or hybrid approaches combining only two methods, which often failed to capture the simultaneous volatility, trend, and nonlinear characteristics of rainfall data. Monthly rainfall data from 2015 to 2024 were analyzed using three individual models: Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Holt's Exponential Smoothing, and Backpropagation Neural Network (BPNN). Two hybrid models, GARCH–Holt and GARCH–Holt–BPNN, were also developed to integrate the advantages of statistical and artificial intelligence methods. Hyperparameter tuning was performed to optimize model performance, and forecasting accuracy was evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Results showed that GARCH effectively captured short-term volatility, Holt followed trends and seasonal patterns, and BPNN modeled nonlinear relationships despite sensitivity to data variations. The GARCH–Holt hybrid improved stability and accuracy compared to individual models, while the GARCH–Holt–BPNN hybrid achieved the highest predictive performance with a MAPE of 1.13%, indicating strong generalization capability. Forecasted rainfall for 2025 revealed seasonal patterns characterized by periods of heavy, moderate, and light rainfall. A MATLAB-based Graphical User Interface (GUI) was developed to facilitate interactive modeling and visualization. Overall, the proposed hybrid GARCH–Holt–BPNN model provides a more robust and reliable forecasting framework by effectively integrating volatility, trend, and nonlinear components, thereby enhancing predictive accuracy and supporting data-driven decision-making in hydrometeorological applications.

1. Introduction

Rainfall is a critical hydrometeorological variable that plays a significant role in maintaining ecosystem stability, food security, and socio-economic sustainability, particularly in tropical regions such as Indonesia, which are strongly influenced by regional atmospheric dynamics. Changes in rainfall intensity and distribution can directly affect water availability, agricultural productivity, and the potential occurrence of hydrometeorological hazards. Therefore, the ability to predict rainfall accurately is a crucial component of environmental management and sustainable development planning [1][2]. The challenge of accurate forecasting is further compounded by the characteristics of rainfall data, which tend to be non-stationary, volatile, and exhibit complex non-linear patterns [3][4]. With the advancement of technology, various statistical and artificial intelligence-based approaches have been extensively developed, including hybrid models that integrate multiple methods to improve forecasting accuracy.

The structural complexity of rainfall patterns increases the risk of prediction errors, which at the operational level can lead to significant economic losses, particularly in agriculture, water resource management, and disaster mitigation. Even short-term prediction inaccuracies can disrupt irrigation systems, affect planting schedules, and increase community vulnerability to floods and droughts [5]. Therefore, forecasting models are required not only to be accurate but also capable of comprehensively representing multiple data characteristics.

Traditional statistical methods, such as ARIMA, have long been used to model hydrological time series; however, they have limitations in capturing complex structures, particularly when data exhibit nonlinear trends and time-varying variance [6]. To address heteroskedasticity, studies by , Zhang et al. [7] and Hamzacebi and Es [8] reported that the application of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to atmospheric and hydrological data produces MAPE values ranging from 10–18%, particularly when the data exhibit extreme fluctuations and dynamically changing variance. In monthly rainfall forecasting, GARCH has proven effective in reducing prediction errors caused by seasonal variability spikes, making its performance comparable to certain nonlinear artificial intelligence models in practice. Nevertheless, GARCH has limitations in modeling long-term trends and complex nonlinear relationships. These findings confirm that GARCH remains a relevant predictive model with high accuracy, particularly when the data are dominated by strong volatility patterns. Its effectiveness lies in its ability to capture volatility changes, which are often a dominant characteristic of both daily and monthly rainfall data.

In addition to variance-based approaches, Holt's Exponential Smoothing method is widely used due to its ability to identify trend and seasonal patterns in hydrological time series. This method provides stability for short- to medium-term forecasting and is frequently applied in monthly rainfall modeling [9]. However, it assumes relatively linear data patterns and is unable to capture nonlinear relationships and high volatility, limiting its ability to represent complex data dynamics. Several studies have shown that Holt and its variants, such as Holt–Winters, can achieve MAPE values in the range of 12–20% for short- to medium-term forecasting [10][11]. Nevertheless, this approach still has limitations in modeling complex nonlinear relationships.

Advances in artificial intelligence have introduced a new paradigm in hydrometeorological forecasting, enabling models to capture non-linear relationships without specific assumptions about data distribution. The Backpropagation Neural Network (BPNN) is among the most widely used algorithms due to its adaptive ability to learn hidden patterns [12][13]. Previous studies indicate that neural network-based models can produce lower errors compared to linear statistical methods for various atmospheric phenomena [14][15]. In chaotic data conditions, BPNN has even been reported to achieve high accuracy, with MAPE ranging from 10–20% [16][17].

The advancement of artificial intelligence has introduced a new paradigm in hydrometeorological forecasting, enabling models to capture nonlinear relationships without strict assumptions regarding data distribution. The Backpropagation Neural Network (BPNN) is one of the most widely used algorithms due to its adaptive capability in learning hidden patterns [12][13]. Previous studies have shown that neural network-based models can produce lower prediction errors compared to linear statistical methods in various atmospheric phenomena [14][15]. However, BPNN also has several limitations, including a tendency toward overfitting, model instability, and suboptimal performance in handling high volatility without adequate preprocessing. Even under chaotic data conditions, BPNN has been reported to achieve relatively high accuracy, with MAPE values ranging from 10–20% [16][17].

Despite the development of various methods, most previous studies still focus on single models or combinations of two methods, such as ARIMA–GARCH, Holt–ANN, or ANN–Fuzzy [18][19][20]. These approaches generally capture only specific characteristics of rainfall data, such as volatility, trend, or nonlinearity, in isolation, and therefore fail to fully represent the overall data dynamics. In reality, rainfall data often exhibit a simultaneous combination of heteroskedastic volatility, seasonal trends, and complex nonlinear relationships. This limitation indicates a research gap in developing models capable of integrating these three characteristics simultaneously within a comprehensive forecasting framework[21][22].

Based on this gap, this study proposes a hybrid approach that integrates GARCH, Holt's Exponential Smoothing, and Backpropagation Neural Network (BPNN) into a unified forecasting framework. The novelty of this study lies in the integration of three methods with distinct strengths, namely the ability of GARCH to capture volatility, Holt to identify trend and seasonality, and BPNN to model complex nonlinear relationships. This integration is expected to improve the accuracy, stability, and robustness of the model compared to single or two-component hybrid approaches. In addition, this study develops a MATLAB-based Graphical User Interface (GUI) as an interactive forecasting system, providing practical value for supporting decision-making in hydrometeorological applications. Specifically, the objectives of this study are: (1) to evaluate the performance of each model; (2) to analyze the accuracy improvement of the proposed hybrid model; and (3) to implement the model in the form of an applicable GUI-based system.

2. Research Method

This study is experimental research designed to examine and compare the predictive performance of several time series forecasting models applied to rainfall data. An experimental approach is employed to directly evaluate the effectiveness of two different models Holt's Exponential Smoothing and the Backpropagation Neural Network (BPNN) by measuring prediction accuracy using standard evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE) under uniform experimental and testing conditions. In addition to model evaluation, this study also incorporates a development component through the creation of a Graphical User Interface (GUI) as a supporting analytical tool, which functions as a decision support system to facilitate practitioners in interactively modeling and forecasting rainfall. Accordingly, this experimental research not only produces an objective comparative evaluation of the three forecasting methods but also delivers an applicative computational tool that can be utilized in data-driven decision-making contexts.

This study utilizes monthly rainfall data collected over the period from January 2015 to December 2024 as the basis for analysis. The dataset consists of quantitative time series data obtained from secondary sources through official institutions, including observational stations of the Indonesian Agency for Meteorology, Climatology, and Geophysics

(BMKG), as well as satellite-based supporting data accessed from NASA's Earth Data Repository for comparative reference. In terms of characteristics, the rainfall data exhibit complex patterns, characterized by non-linear and non-stationary behavior, as well as heteroskedasticity reflected in time-varying volatility, particularly during transitions between periods of extreme rainfall and dry conditions. This complexity necessitates the use of more advanced modeling techniques to capture the underlying variability dynamics. From a measurement perspective, rainfall data are measured on an interval scale, allowing for uniform intervals without an absolute zero, and operationally can be classified into rainfall events (values > 0) and non-rainfall events (values = 0) to support discrete analysis as well as volatility modeling.

To enhance model performance and ensure reproducibility, hyperparameter tuning was performed for each forecasting model applied in this study. For the GARCH model, several candidate specifications, including GARCH (1,1), GARCH (1,2), and GARCH (2,1), were evaluated, and the optimal model order was selected based on the lowest values of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). In the Holt's Exponential Smoothing method, the smoothing parameters associated with the level and trend components were optimized through an iterative search within the interval of 0 to 1, with the optimal parameter combination determined by minimizing the RMSE value on the training dataset. For the Backpropagation Neural Network (BPNN), hyperparameter tuning involved adjusting the number of hidden neurons, learning rate, and number of training epochs. The hidden layer size was experimentally varied between 5 and 20 neurons, while the learning rate ranged from 0.01 to 0.1. The final network configuration was selected based on the lowest RMSE obtained during the training phase while maintaining stable convergence throughout the learning process.

2.1 Generalized Autoregressive Conditional Heteroskedasticity

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) is employed to model time series data that exhibit time-varying variability (heteroskedasticity). This method is highly relevant for rainfall data, which often experience extreme fluctuations, as GARCH is capable of capturing the dynamics of non-constant variance [23]. The most commonly used GARCH (1,1) model is mathematically formulated in Equation 1:

$$\sigma^2 t = \omega + \alpha\epsilon^2 t_{-1} + \beta\sigma^2 t_{-1} \tag{1}$$

In the GARCH framework, $\sigma^2 t$ represents the conditional variance at time t, which reflects the level of volatility or dispersion of the data at that period. The term $\epsilon^2 t_{-1}$ denotes the squared residual (shock) from the previous period, capturing the short-term impact of recent shocks on current volatility. Meanwhile, $\sigma^2 t_{-1}$ refers to the variance in the preceding period, which governs the influence of past volatility on present conditions. The parameters $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$ are used to control the volatility dynamics of the time series. A higher value of α indicates greater sensitivity to recent shocks, whereas a larger value of β implies that volatility persists over time. The combination of these components enables the GARCH model to generate variance estimates that adapt to fluctuation patterns in rainfall data, particularly when significant changes in variability occur over time [24].

2.2 Holt's Exponential Smoothing

Holt's Exponential Smoothing method is used to model time series data that exhibit a trend component [25]. The most commonly applied variant for rainfall forecasting is the Holt–Winters model, which incorporates a seasonal component to capture recurring patterns in the time series. The updating equation for the level component is presented in Equation 2.

$$L_t = \alpha Y_t + (1-\alpha) + \left(L_{t_{-1}} + T_{t_{-1}}\right) \tag{2}$$

In Holt's Exponential Smoothing method, L_t represents the level component, which describes the baseline value of the time series at period t, while T denotes the trend component that reflects the direction and rate of change of the series over time. The actual observed value at period t, denoted by Y_t serves as the reference for updating both components. The smoothing parameter α, with a range of $0 \leq \alpha \leq 1$, controls the degree of smoothness in updating the level component, where higher values of α assign greater weight to more recent information, whereas lower values preserve the influence of historical data [26]. Collectively, these elements operate simultaneously to produce time series estimates and forecasts that are more adaptive to evolving patterns in the data.

2.3 Backpropagation Neural Network

Backpropagation Neural Network (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 [27]. The multilayer structure of BPNN allows this model to capture nonlinear patterns that are difficult to identify by conventional statistical models, making it very useful for data that has high fluctuations or nonlinear behavior. The training process with backpropagation iteratively adjusts the weights to minimize the error between the prediction and the actual data, thereby improving the accuracy of the model [28]. The advantage of BPNN also lies in its flexibility in handling various types of data, including time series. The mathematical model of BPNN is in accordance with Equations 3, 4, 5, and 6.

Output neuron

$$y_j = f\left(\sum_{i=1}^{n} w_{ij}x_i + b_j\right) \tag{3}$$

Where y_j is the output of neuron j, x_i is the input of neuron i, w_{ij} is the weight from neuron i to neuron j, b_j is the bias of neuron j, and $f(\cdot)$ is the activation function.

Error function (Loss Function)

$$\text{MSE}=\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y_t})^2 \tag{4}$$

Where y_t is the actual temperature at time t, N is the temperature predicted by BPNN, and N is the amount of data.

Update weight (Backpropagation)

$$w_{ij}^{\text{new}} = w_{ij}^{\text{old}} - \eta\frac{\partial E}{\partial w_{ij}} \tag{5}$$

$$b_j^{\text{new}} = b_j^{\text{old}} - \eta\frac{\partial E}{\partial b_j} \tag{6}$$

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

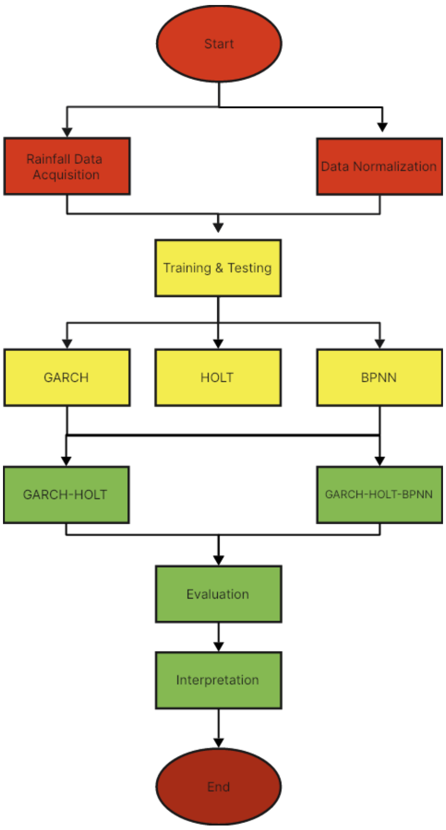

Figure 1. Research Workflow

Figure 1 illustrates the systematic stages in rainfall forecasting, starting with the rainfall data acquisition process sourced from official institutions, followed by the data normalization stage to standardize the scale and enhance modeling stability. The processed data is then divided into training and testing stages to objectively evaluate the predictive capability of the models. In this stage, three primary forecasting methods are applied, namely Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Holt's Exponential Smoothing (HOLT), and Backpropagation Neural Network (BPNN) as single models. The results from these models are further developed through hybrid approaches, specifically GARCH–HOLT and GARCH–HOLT–BPNN, to combine the advantages of each method in capturing volatility, trend, and non-linear patterns of rainfall data. All generated models are subsequently evaluated using predefined prediction error metrics, and the evaluation results are interpreted to assess model performance and implications in the context of rainfall forecasting.

2.4 Forecast Evaluation Metrics

To evaluate the forecasting performance of each model, three commonly used error metrics were employed: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics are widely used in time-series forecasting to quantify the deviation between predicted and actual values.

Mean Squared Error (MSE) measures the average of the squared differences between predicted values and actual observations, providing an overall indication of prediction accuracy. RMSE represents the square root of MSE and expresses the prediction error in the same unit as the original data, making it easier to interpret in practical applications. Meanwhile, MAPE expresses the average absolute error as a percentage of the actual values, allowing comparisons across different forecasting models. The mathematical formulations of the evaluation metrics used to assess forecasting performance are presented in Equation 7, Equation 8, and Equation 9.

$$MSE = \left({}^{1}/_{N}\right) \sum (y_t - \hat{y}_t)^2 \tag{7}$$

$$RMSE = \sqrt{\left({}^{1}/_{N}\right) \sum (y_t - \hat{y}_t)^2} \tag{8}$$

$$MAPE = \left({}^{100}/_{N}\right) \sum |(y_t - \hat{y}_t)/y_t| \tag{9}$$

where y_t represents the actual rainfall value at time t, $\hat{y}_t$ denotes the predicted value, and N is the number of observations. Lower values of MSE, RMSE, and MAPE indicate better forecasting performance.

Tabel 1. Classification of Accuracy Levels Based on MAPE

Percentage	Decimal	Category
< 10%	< 0.10	Very Accurate
10% – 20%	0.10 – 0.20	Accurate
20% – 30%	0.20 – 0.30	Less Accurate
> 30%	> 0.30	Not Accurate

Table 1 presents the classification of forecasting model accuracy levels based on the Mean Absolute Percentage Error (MAPE), which is a commonly used evaluation metric for measuring the average percentage of absolute errors between actual and predicted values. In the table, the category "Very Accurate" is assigned to MAPE values of less than 10 percent or below 0.1 in decimal form, indicating that the difference between predicted and actual values is very small and that the model demonstrates excellent predictive capability. The "Accurate" category applies to MAPE values ranging from 10 to 20 percent or 0.1 to 0.2, suggesting that the model is still able to provide reasonably precise predictions. The "Less Accurate" category includes MAPE values between 20 and 30 percent or 0.2 to 0.3, indicating a relatively high level of prediction error and reduced reliability of the model. Meanwhile, the "Not Accurate" category is assigned to MAPE values exceeding 30 percent or greater than 0.3, reflecting very large prediction errors and poor model performance in representing the actual data.

3. Results and Discussion

The dataset used in this study consists of 120 monthly rainfall observations covering the period from 2015 to 2024. These data represent long-term rainfall conditions and were selected to capture both temporal variability and recurring seasonal patterns that typically occur on an annual basis. The rainfall data are presented in tabular form to provide an initial descriptive overview of the general patterns, value ranges, and fluctuations observed across months and years prior to conducting further analysis and modeling. This preliminary descriptive analysis serves as an important foundation for understanding the underlying characteristics of the time series before applying forecasting methods such as GARCH, Holt's Exponential Smoothing, and Backpropagation Neural Network (BPNN).

Table 2. Monthly Rainfall Data

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2015	340	320	300	240	180	110	85	70	90	150	260	330
2016	360	335	315	255	190	120	95	80	105	165	275	350
2017	330	305	285	230	170	100	80	65	85	140	245	320
2018	350	330	305	245	185	115	90	75	95	155	270	340
2019	370	350	325	265	200	130	105	90	110	175	290	360
2020	380	360	335	275	210	140	115	95	120	185	300	370
2021	320	300	280	235	180	110	90	75	95	155	255	330
2022	340	320	295	245	185	115	90	75	100	165	265	340
2023	390	370	345	285	220	150	120	105	130	195	310	380
2024	375	355	330	270	205	135	110	95	120	180	290	365

Based on the data presented in Table 2, a forecasting system was developed using a Graphical User Interface (GUI) in MATLAB 2017b to facilitate model analysis and evaluation. The development of the GUI is not merely implementation-oriented but also serves as an integrated platform that enables systematic comparative analysis across different forecasting methods. This system incorporates the GARCH, Holt's Exponential Smoothing, BPNN, and the hybrid GARCH–Holt–BPNN models. The results from the training and testing of the data are subsequently presented as the basis for evaluating model performance in producing accurate forecasts, as shown in Table 3.

Table 3. Training and Testing Data Results

Algoritma	MSE	RMSE	MAPE (%)
GARCH	0.36	0.60	2.14
Holt	0.22	0.47	1.23
BPNN	0.29	0.54	1.46
GARCH–Holt	0.41	0.64	1.96
GARCH–Holt–BPNN	0.26	0.51	1.13
Algoritma	MSE	RMSE	MAPE (%)
GARCH	0.51	0.71	5.90
Holt	0.29	0.54	1.21
BPNN	4.61	2.14	6.56
GARCH–Holt	0.43	0.66	1.97
GARCH–Holt–BPNN	0.15	0.39	1.13

The evaluation results on the training dataset 80% indicate that Holt's method achieves the lowest prediction error among the single models, followed by BPNN and GARCH. This finding suggests that smoothing-based approaches are more effective in capturing trend and seasonal patterns in rainfall data compared to volatility-based methods. However, the proposed hybrid GARCH–Holt–BPNN model demonstrates superior performance overall, indicating that the integration of volatility modeling, trend estimation, and nonlinear learning provides a more comprehensive representation of rainfall dynamics. Although the numerical improvement appears relatively modest, it reflects enhanced model accuracy and improved capability in capturing complex data patterns.

On the testing dataset 20%, the hybrid GARCH–Holt–BPNN model again demonstrates the best overall performance, outperforming both single and two-component hybrid models. This result indicates that the proposed model possesses superior generalization capability, particularly when applied to unseen data. In contrast, the increased error observed in the BPNN model suggests potential overfitting, while the GARCH model appears less effective in capturing seasonal structures. These findings highlight the importance of integrating multiple modeling approaches to effectively represent the complex dynamics of rainfall data.

Based on the simulation results obtained, the GARCH, Holt, and BPNN methods demonstrate good performance in forecasting monthly rainfall. The relatively low values of MSE, RMSE, and MAPE for each method indicate that the prediction errors are minimal, thus effectively representing rainfall patterns. The GARCH model is effective in capturing volatility and sharp fluctuations in rainfall data, the Holt method can follow trend tendencies steadily, while BPNN excels in learning complex nonlinear patterns in hydrometeorological data. Evaluations on both training and testing data show consistent and stable performance, suggesting that these three methods are efficient and suitable for monthly rainfall forecasting. Therefore, GARCH, Holt, and BPNN can be considered reliable approaches for producing accurate rainfall predictions.

During the training process, the model iteratively adjusts its parameters to ensure that the predicted results closely align with the actual data. The closeness between the actual and predicted data is evaluated using error metrics such as MSE, RMSE, MAPE, and Accuracy. Lower error values indicate better model performance in approximating or representing the patterns present in the actual data. Below are the Training and Testing results for monthly rainfall forecasting using the GARCH, Holt, BPNN, GARCH–Holt, and GARCH–Holt–BPNN methods.

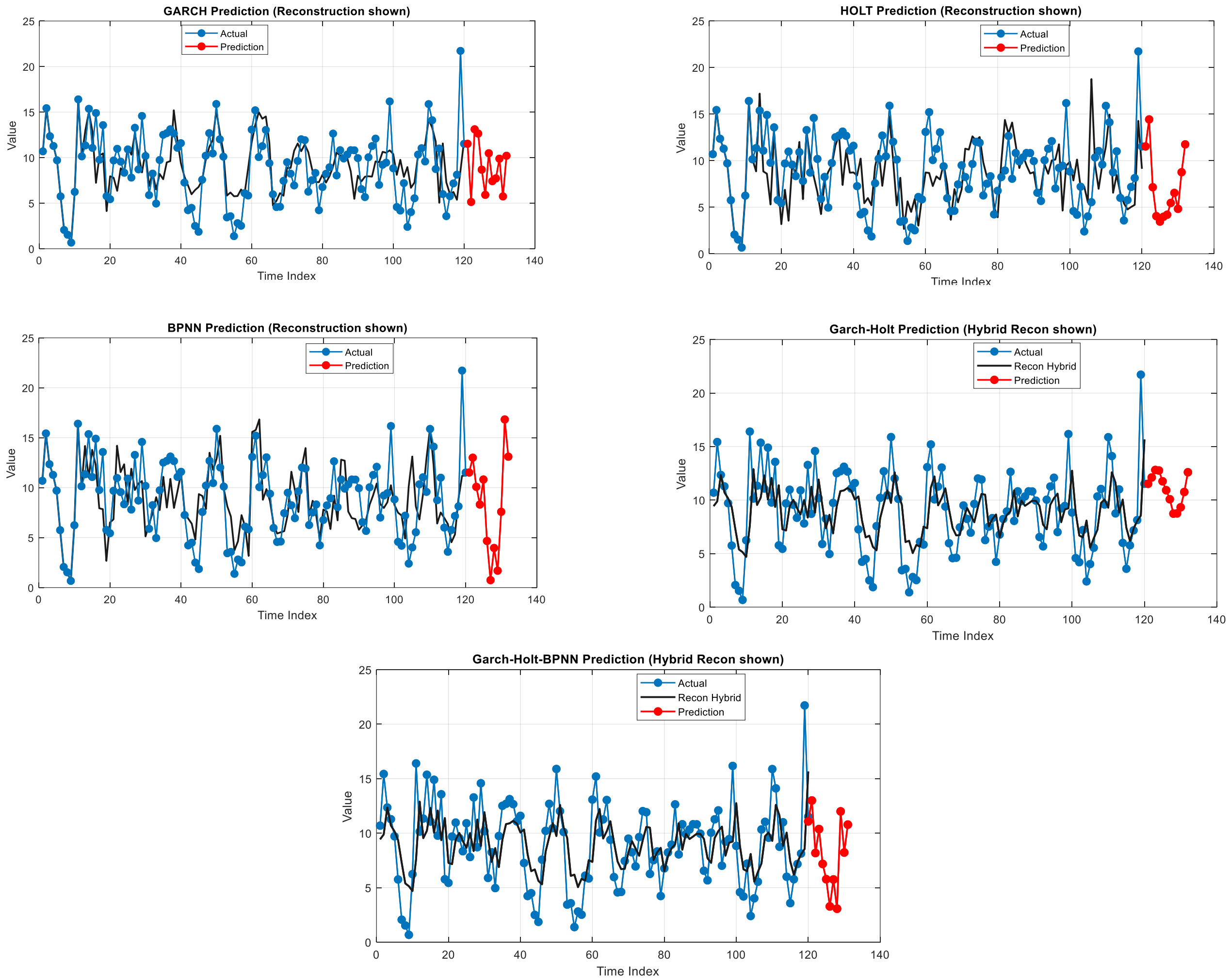

Figure 2. GARCH, HOLT BPNN, GARCH-HOLT, and GARCH-HOLT-BPNN Training Result Graph

Figure 2 illustrates the rainfall forecasting performance on the training dataset across the five evaluated models. The GARCH model is able to capture general rainfall fluctuations; however, deviations are observed due to its sensitivity to volatility. Holt's method demonstrates a stronger ability to follow the underlying trend and short-term variations, indicating its effectiveness in modeling seasonal rainfall patterns. The BPNN model captures nonlinear relationships in the data, although minor deviations remain. The hybrid GARCH–Holt model reflects an integration of volatility and trend components but does not outperform the Holt model when applied independently. In contrast, the proposed GARCH–Holt–BPNN model exhibits the most stable and consistent performance, effectively capturing the underlying rainfall dynamics. This result highlights that the integration of volatility modeling, trend estimation, and nonlinear learning provides a more comprehensive representation of the data, leading to improved forecasting performance compared to both single and two-component hybrid models.

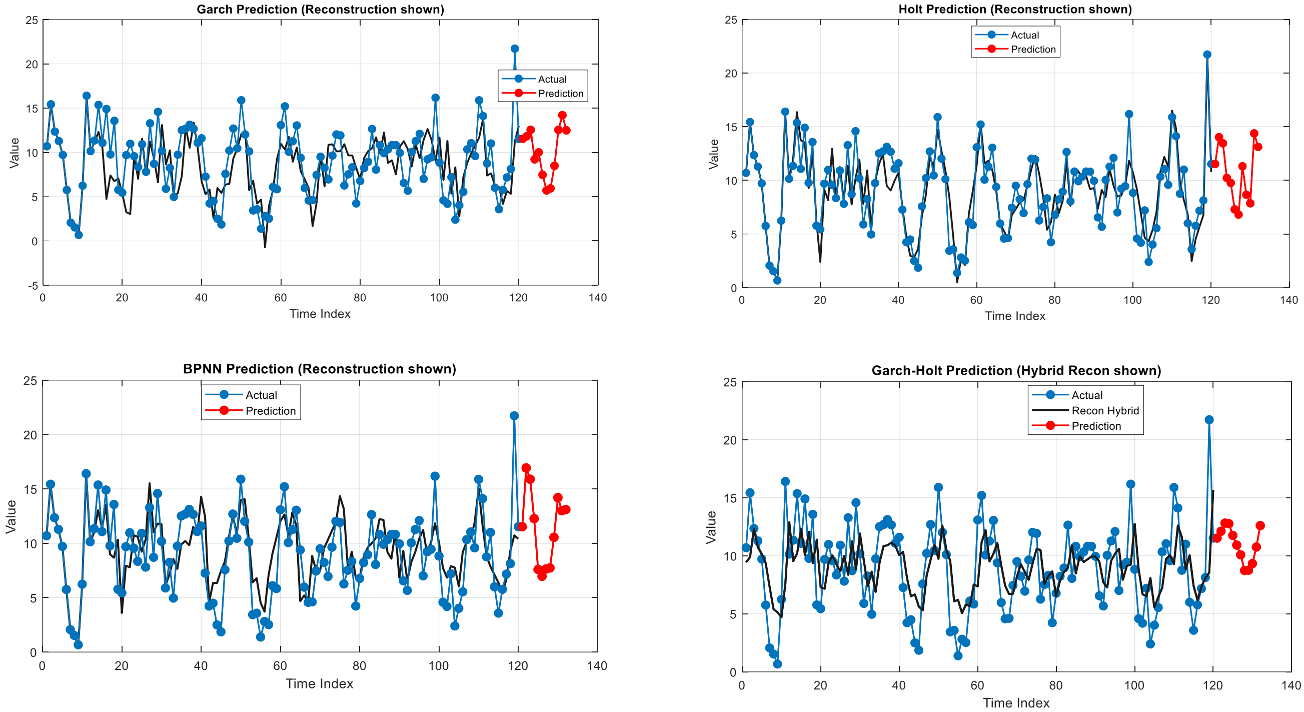

Figure 3. GARCH, HOLT, BPNN, GARCH-HOLT Testing Results Graph

Figure 3 presents the rainfall forecasting results on the testing dataset for the five evaluated models. The GARCH approach captures overall variability but shows noticeable discrepancies due to its sensitivity to changing variance. Holt's method provides more consistent tracking of rainfall trends, demonstrating its strength in representing seasonal behavior. The BPNN model identifies nonlinear patterns; however, its performance declines when applied to unseen data, indicating limited robustness. The hybrid GARCH–Holt model offers a more balanced approximation by combining volatility and trend components, improving performance relative to some individual models. The proposed GARCH–Holt–BPNN model achieves the highest level of accuracy and stability, reflecting its ability to represent rainfall dynamics more effectively. This outcome emphasizes that combining statistical and machine learning approaches leads to improved generalization and reliability in forecasting applications.

After obtaining relatively stable results from the GARCH, Holt, BPNN, and GARCH–Holt models as shown in Figure 3, this study further extends the analysis by developing a more advanced hybrid model, namely GARCH–Holt–BPNN, which integrates the strengths of volatility modeling, trend capturing, and the nonlinear learning capability of neural networks. The rainfall forecasting results produced by the GARCH–Holt–BPNN model are presented in Figure 4.

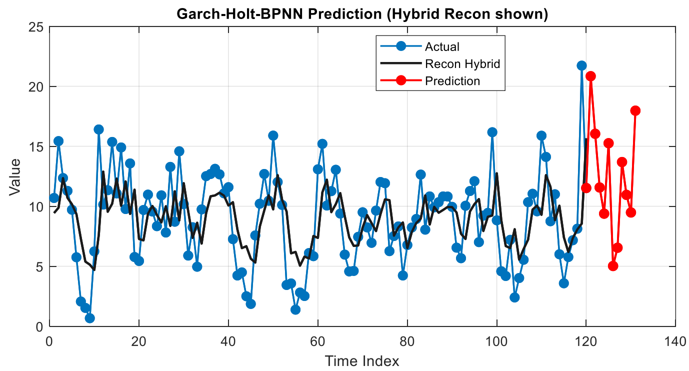

Figure 4. GARCH-HOLT-BPNN Testing Result Graph

Figure 4 illustrates the performance of the proposed hybrid GARCH–Holt–BPNN model in rainfall forecasting on the testing dataset. The visualization shows that the model is able to closely follow the actual rainfall patterns, indicating a stable and consistent fit. This result demonstrates that the integration of volatility modeling, trend estimation, and nonlinear learning enables the model to effectively capture complex rainfall dynamics. The superior performance of the proposed model is further reflected in its robustness and strong generalization capability when applied to unseen data, confirming its effectiveness compared to both single and two-component hybrid models.

Based on the analysis results, each model demonstrates different capabilities in representing the fluctuating behavior of rainfall data. The GARCH model effectively captures volatility and sudden fluctuations; however, its performance is limited in representing seasonal structures. Holt's method shows more stable and reliable performance in adapting to short-term trends and seasonal patterns, confirming the effectiveness of smoothing-based approaches for rainfall forecasting. The BPNN model is capable of capturing nonlinear relationships, although its sensitivity to highly variable data leads to reduced robustness when applied to unseen conditions.The hybrid GARCH–Holt model provides a more balanced representation by integrating volatility and trend components, resulting in improved stability compared to individual models. Nevertheless, the proposed GARCH–Holt–BPNN model demonstrates the best overall performance, as it combines volatility modeling, trend estimation, and nonlinear learning within a unified framework. This integration enables the model to more effectively capture the complex dynamics of rainfall data, leading to improved accuracy and stronger generalization capability. These findings confirm that the proposed hybrid model outperforms both single and two-component hybrid approaches, highlighting its robustness and effectiveness for rainfall forecasting. From a practical perspective, this model shows strong potential for application in water resource planning, agricultural management, and hydrometeorological risk mitigation.

The following presents the results of monthly rainfall forecasting for the year 2025. These data provide an overview of rainfall variability throughout the year, which can serve as a reference for understanding seasonal patterns and supporting planning processes in various sectors, such as agriculture, water resources management, and hydrometeorological disaster mitigation. The presented forecasts are based on the classification of monthly rainfall into three categories low, normal, and high according to the seasonal patterns generated by the model. The forecasting results are summarized in Table 4.

Table 4. Rainfall Prediction Results for 2025

Month	Rainfall 2025	Rainfall Category
January	240.3 mm	Heavy Rain
February	215.6 mm	Heavy Rain
March	190.4 mm	Moderate Rain
April	140.2 mm	Moderate Rain
May	95.8 mm	Light Rain
June	55.4 mm	Light Rain
July	40.7 mm	Light Rain
August	45.9 mm	Light Rain
September	75.6 mm	Light Rain
October	120.8 mm	Moderate Rain
November	180.9 mm	Moderate Rain
December	245.1 mm	Heavy Rain

Table 4 indicates that the predicted rainfall for 2025 follows a clear and consistent seasonal pattern. Rainfall is highest at the beginning of the year, representing the peak of the rainy season, before gradually decreasing during the transitional months. The mid-year period is characterized by low rainfall, reflecting the dry season, while rainfall increases again toward the end of the year, marking the onset of the next rainy season. This pattern demonstrates the model's capability to accurately capture seasonal rainfall dynamics. From a practical perspective, these findings provide valuable insights for agricultural planning, water resource management, and hydrometeorological risk mitigation, particularly in anticipating periods of high rainfall and potential drought conditions.

Based on the analysis results, each model demonstrates distinct capabilities in representing the fluctuating behavior of rainfall data. The GARCH model effectively captures volatility and the heteroskedastic nature of rainfall time series, where variance changes between wet and dry periods; however, its performance is limited in representing seasonal structures, indicating that volatility modeling alone is insufficient to describe rainfall dynamics comprehensively. In contrast, Holt's method shows stronger performance in capturing trend and seasonal transitions, highlighting the effectiveness of smoothing-based approaches for modeling gradual changes in rainfall intensity. This makes it particularly suitable for short-term operational applications, such as agricultural planning and irrigation management. Meanwhile, the BPNN model is capable of capturing nonlinear relationships but exhibits sensitivity to data variability, leading to reduced robustness when applied to unseen data.

The introduction of hybrid models leads to noticeable performance improvement. The GARCH–Holt model provides a more balanced representation by integrating volatility and trend components, enabling the model to capture both abrupt fluctuations and gradual seasonal patterns. However, the most significant improvement is achieved by the proposed GARCH–Holt–BPNN model, which integrates volatility modeling, trend estimation, and nonlinear learning within a unified framework. This integration allows the model to more effectively capture the complex dynamics of rainfall data, resulting in improved accuracy, robustness, and generalization capability. Although the numerical improvement over Holt's method appears modest, the hybrid approach offers greater stability when applied to unseen data.

From a practical perspective, even small improvements in forecasting accuracy can significantly enhance decision-making in water resource management, agricultural planning, and flood risk mitigation, particularly in regions with high rainfall variability. Therefore, the proposed hybrid model not only provides superior predictive performance but also offers a reliable and applicable solution for supporting hydrometeorological decision-making processes.

These findings are consistent with previous studies suggesting that hybrid forecasting models often outperform single-model approaches because they combine complementary modeling strengths. Hybrid models are able to simultaneously address multiple structural characteristics of rainfall time series, including volatility, seasonality, and nonlinear dynamics. Earlier studies combining smoothing techniques and neural networks have shown that hybrid approaches can better capture intermittent rainfall patterns than individual models alone [29][30]. Similarly, recent hydrological forecasting research emphasizes that hybrid modeling frameworks are particularly effective for handling non-stationarity, variability, and heteroskedasticity in rainfall data [31][32].

Therefore, beyond providing improved statistical forecasting performance, the proposed GARCH–Holt–BPNN hybrid model also offers important practical implications for hydrometeorological management. More reliable rainfall predictions can support better decision-making in water resource management, irrigation planning, flood mitigation strategies, and climate adaptation policies. In regions with high rainfall variability such as Indonesia, forecasting systems that integrate statistical and artificial intelligence approaches can serve as valuable tools for improving environmental resilience and supporting sustainable development planning.

4. Conclusion

This study demonstrates that each forecasting method has distinct strengths in representing rainfall dynamics. The GARCH model effectively captures volatility but is limited in modeling seasonal patterns, while Holt's Exponential Smoothing provides stable performance in capturing trends and seasonality. The BPNN model is capable of identifying nonlinear relationships but shows sensitivity to data variability, which may reduce robustness on unseen data. The integration of these methods through hybrid approaches significantly improves forecasting performance. In particular, the proposed GARCH–Holt–BPNN model achieves the best overall results by combining volatility modeling, trend estimation, and nonlinear learning within a unified framework, consistently producing the lowest prediction errors and demonstrating strong generalization capability. Although the numerical improvement over Holt's method is modest, it reflects enhanced robustness in capturing complex rainfall patterns. The 2025 rainfall prediction further confirms the model's ability to represent seasonal dynamics consistent with typical tropical climate behavior. Additionally, the development of a MATLAB-based GUI enhances the practical contribution of this study by providing an interactive platform for model analysis and implementation. Overall, the proposed hybrid model offers a robust and reliable framework for rainfall forecasting and has strong potential to support data-driven decision-making in water resource management, agriculture, and hydrometeorological risk mitigation.

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