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FORECASTING STOCK PRICES OF PT. BANK RAKYAT INDONESIA USING THE HYBRID ARIMA-BACKPROPAGATION NEURAL NETWORK METHOD

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Abstract: *PT. Bank Rakyat Indonesia (Persero) Tbk is classified as a blue-chip stock. Although investing in BRI shares has the potential to generate profits, stock price fluctuations can pose risks, making forecasting necessary. The ARIMA model is frequently used to predict such fluctuations, but struggles to capture non-linear patterns. ARIMA is combined with an Artificial Neural Network (ANN), specifically the Backpropagation Neural Network, to address this issue and improve forecasting accuracy. Although Backpropagation is weak in slow convergence, this can be overcome using the Conjugate Gradient Powell Beale (CGB) algorithm. The research results show that the closing stock price data of BRI from January 2023 to February 2024 produced an ARIMA (1,1,1)-Backpropagation [4-4-1] model with higher accuracy, achieving a MAPE of 2.516% and RMSE of 200.1592, Relative to the standalone ARIMA (1,1,1) model, which had a MAPE of 6.203% and RMSE of 421.5896.*

***Keywords*:** *Stock Price, Hybrid, ARIMA, Backpropagation Neural Network.*

1. INTRODUCTION

Stock prices are indicators used to manage a company's performance, reflecting the performance of the company itself. The higher the stock price, the greater the investor interest, which can generate capital gains and enhance the company's image. The most sought-after stock sector in Indonesia is banking [1]. PT. Bank Rakyat Indonesia (Persero) Tbk is one of the prominent companies in the financial sector, especially in the banking industry [2]. Its stock investments consist of blue-chip stocks, which investors highly favor due to being shares of high-quality companies [3]. Stock investments in this bank present both opportunities for profit and risks of loss due to stock price fluctuations. Inadequate monitoring of stock movements by investors can result in financial losses. Therefore, forecasting becomes a critical tool for investors to predict future stock trends and optimize their returns.

One of the forecasting models in statistics is the time series model, which can be divided into two categories. The first category refers to statistical mathematical models, such as ARIMA (Autoregressive Integrated Moving Average). In contrast, the second category includes models like ANN (Artificial Neural Network), which are based on artificial intelligence [4] . The ARIMA method is used for data with linear characteristics, limiting its ability to handle non-linear patterns. Artificial Neural Networks (ANN) are required to address this limitation, as they can predict non-linear data [5]. The ANN method commonly used is the Backpropagation Neural Network method. Although Backpropagation Neural Networks conventionally utilize the Feed Forward Neural Network (FFNN) algorithm for weight updates, they exhibit inherent limitations in parameter sensitivity that result in substantially delayed convergence rates and compromised output accuracy. Consequently, optimization techniques are required to enhance training efficiency [6]. The Conjugate Gradient Powell-Beale (CGB) algorithm represents an effective optimization approach to mitigate these backpropagation limitations.

According to [7], the combination of ARIMA and Artificial Neural Network models is chosen for three main reasons. First, applying either linear or nonlinear models is often tricky in time series data, so using a hybrid (combined) model can be a more straightforward or practical option. Second, time series data is typically not entirely linear or nonlinear but includes elements of both. As a result, a merged approach can effectively address time series data that contains both linear and nonlinear trends. Third, various forecasting literature sources

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emphasize that no single model performs optimally or best under all conditions. Thus, it can be concluded that model combination can improve forecasting accuracy by leveraging the strengths of each model.

Research on hybrid methods has been widely conducted before, such as the study [8], which compared the hybrid ARIMA-NN model and the Hybrid ARIMA-GARCH model for forecasting farmer exchange rate data in Gorontalo Province, with the results showing that the hybrid ARIMA-NN model performed better. The result is in line with the research conducted by [9] “he Application of the Hybrid ARIMA-ANN Method to Predict the Stock Price of PT. BNI (Persero) Tbk.". Additionally, it aligns with the study by [10], which compared the ARIMA and Hybrid ARIMA-ANN models in forecasting tuberculosis occurrences among children in Homa Bay Turkana County, Kenya, as well as the research [11], "Forecasting The Price Of Sepinggan Yakin Mix Crude Oil Using Autoregressive Integrated Moving Average-Neural Network Hybrid Model". Based on several previous studies, the hybrid ARIMA-Backpropagation Neural Network (BPNN) method has demonstrated superior performance to single modeling approaches in time series analysis. Therefore, this study aims to model the stock prices of BRI using a hybrid ARIMA–BPNN approach to evaluate its forecasting accuracy. The hybrid method is selected due to its ability to combine the strengths of both models, which complement each other. The ARIMA model accounts for the linear structure of time series data, leaving residuals likely containing nonlinear elements. These residuals are then modeled with a Backpropagation Neural Network to enhance forecasting accuracy. In implementing the BPNN, the Conjugate Gradient Powell-Beale (CGB) optimization algorithm is employed to enhance the learning process's convergence speed and computational efficiency. By integrating both methods, this study is expected to yield more accurate forecasts of the stock prices of PT. Bank Rakyat Indonesia (Persero) Tbk.

2. METHODOLOGY

2.1. Data Source

This study uses daily closing stock price data of PT. Bank Rakyat Indonesia (Persero) Tbk from January 2023 to February 2024 was obtained from the website *https://finance.yahoo.com*. The data were analyzed using RStudio version 4.1.1, with the following packages: TSA, tseries, lmtest, forecast, nortest, MASS, car, and timeSeries for ARIMA modeling, and the nnet package for hybrid ARIMA-Backpropagation Neural Network modeling.

2.2. Stages of Research

In the analysis process, the data analysis procedure involves the combination of the ARIMA method and the Backpropagation Neural Network:

2.2.1. ARIMA Modeling

In this step, the process begins by inputting the research data and creating a time series plot. Then, stationarity testing is conducted by examining the variance stationarity of the data through a Box-Cox plot and the ADF (Augmented Dickey-Fuller) test for the mean. Transaction and differencing are applied to the mean if the variance is not stationary. Next, a preliminary ARIMA model is set by observing the ACF and PACF plots, followed by parameter estimation and significance testing for the AR and MA components. Through this process, a model is obtained and subjected to model diagnostics, including residual assumption testing using the Ljung-Box test to identify whether the data exhibit white noise characteristics. The best model is then selected by considering the smallest AIC (Akaike’s Information Criterion) value. The selected ARIMA model will serve as the basis for forecasting, and its residuals will be utilized in constructing the hybrid model. The AIC calculation formula is outlined below [12] :

$$AIC = -2L(.) + 2M \tag{1}$$

where M is the number of estimated parameters in the model.

2.2.3. Hybrid ARIMA-Backpropagation Neural Network Modeling

The steps involved in the hybrid ARIMA-Backpropagation Neural Network model are as follows.

1. Normalize the data and input the residual data from the ARIMA model as input for the Backpropagation Neural Network.
2. Design the Backpropagation Neural Network model using the Conjugate Gradient Powell Beale algorithm.
3. Forecast using the Backpropagation Neural Network with the Conjugate Gradient Powell Beale algorithm.
4. Combine the ARIMA forecast and the Backpropagation Neural Network forecast to obtain the hybrid forecast result.

After obtaining the best model from each model, the next step is to evaluate the model by assessing its accuracy through the Mean Absolute Percentage Error (MAPE) with the following formula [13]:

$$MAPE = \frac{1}{m}\sum_{t=1}^{m}\left|\frac{\left(A_t - \hat{A}_t\right)}{A_t}\right| \times 100\% \tag{2}$$

where m is the number of observations, A_t is actual data, and $\hat{A}_t$is forecast data.

2.3. ARIMA Method

According to [14], ARIMA (Autoregressive Integrated Moving Average), frequently termed the Box-Jenkins technique, is a time series modeling technique composed of two components: AR (Autoregressive) and MA (Moving Average). he ARIMA model is denoted as ARIMA (p, d, q), where *p* indicates the order of the AR process, *d* represents the number of differencing, and *q* denotes the order of the MA process. Nonstationary time series data undergoes the differencing technique d times to achieve stationarity. This step is included in the ARIMA (p, d, q) model [15]:

$$\phi_p\,(B)(1-B)^d\,\mathrm{A}_t = \theta_0 + \theta_q\,(B)\alpha_t \tag{3}$$

where:

$$\theta_0 = \mu(1 - \phi_1 - \cdots - \phi_p) \tag{4}$$

$\phi_p\,(B)$: The autoregressive polynomial of order *p*, B : the backshift operator, A_t : The value of the time series variable at time *t*, $\theta_q\,(B)$: Moving Average polynomial of order q, α_t : *white noise* and, d: the number of differencing.

2.4. Artificial Neural Network Method

Artificial Neural Networks (ANN) have the advantage of providing high forecasting accuracy for nonlinear data models, in addition to their excellent pattern recognition capabilities [16]. The characteristics of ANN include the structure or pattern of relationships between neurons, known as the architecture, techniques for determining the weights of these relationships, known as training or algorithms, and the functions used to activate the neurons [17]. The ANN model is structured with an input layer, one or more hidden layers, and an output layer [18].

The supervised learning method commonly used in artificial neural networks with a multilayer structure to adjust the weight values in the hidden layers is the Backpropagation algorithm [19]. During the training process, the Conjugate Gradient Powell Beale (CGB) algorithm is used to enhance the performance speed of the Backpropagation algorithm, as the Backpropagation algorithm can be time-consuming. The training process is repeated until a stopping condition is reached, which can be either a specified number of iterations or an acceptable error threshold.

The normalization process is performed before processing with the ANN using the following equation [20]:

$$A't = \frac{A - A_{min}}{A_{max} - A_{min}} \tag{5}$$

where A_{min} : minimum value of the observation, A_{max} : maximum value of the observation, A' : normalized value of the observation, A : observation value before normalization.

2.5. Hybrid ARIMA-Backpropagation Neural Network Method

The hybrid method is an approach that combines two or more processes or models, leveraging the strengths of each model. This study combines the ARIMA method and Backpropagation Neural Network, where the ARIMA model generates estimates referred to as the linear component. In contrast, the model's residuals are considered the nonlinear component. After the linear component is formed, the next phase entails constructing the nonlinear model using the linear model's residuals.

The general equation for the hybrid ARIMA-Backpropagation Neural Network model is as follows [21]:

$$\hat{Z}_t = \hat{L}_t + \hat{N}_t \tag{6}$$

where $\hat{Z}_t$: hybrid forecast, $\hat{L}_t$: linear component, and $\hat{N}_t$: nonlinear component obtained from the residual forecast of the linear component.

3. RESULT AND DISCUSSION

Before the analysis is performed, the data is divided into training data covering January 2023 to January 2024 and testing data for February 2024. Below is the stock price plot for PT. Bank Rakyat Indonesia (Persero) Tbk.

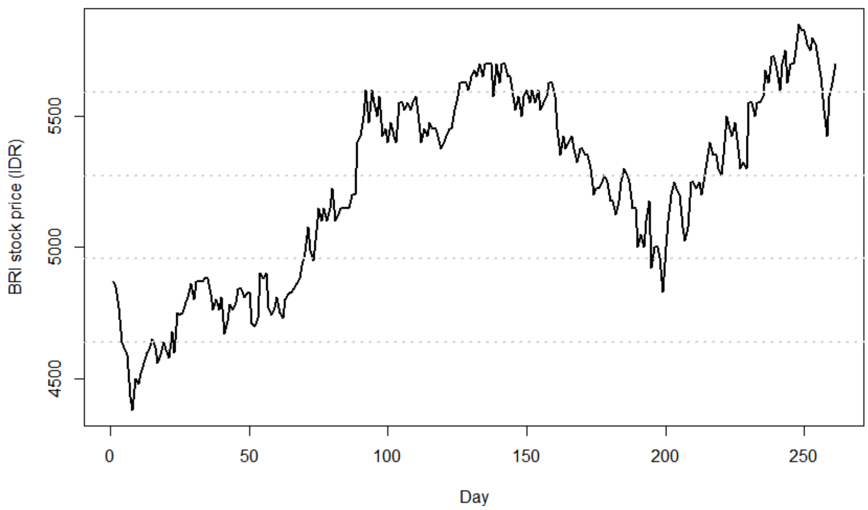

Figure 1. Stock Price Data Plot for PT. Bank Rakyat Indonesia (Persero) Tbk
Source: Rstudio version 4.1.1

In Figure 1, it is shown that the training data of the stock price of BRI exhibits both increasing and decreasing trends, indicating the non-stationary nature of the data. The variance stationarity of the data is shown in the Box-Cox plot.

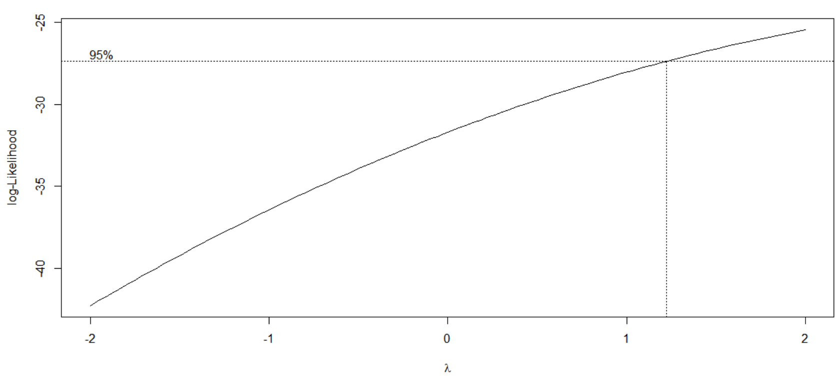

Figure 2. Training Data Plot for Variance Stationarity Analysis
Source: Rstudio version 4.1.1

Figure 2 shows that the data exhibits non-stationarity in variance due to the lambda value, requiring transformation. Below is the Box-Cox plot after the data transformation.

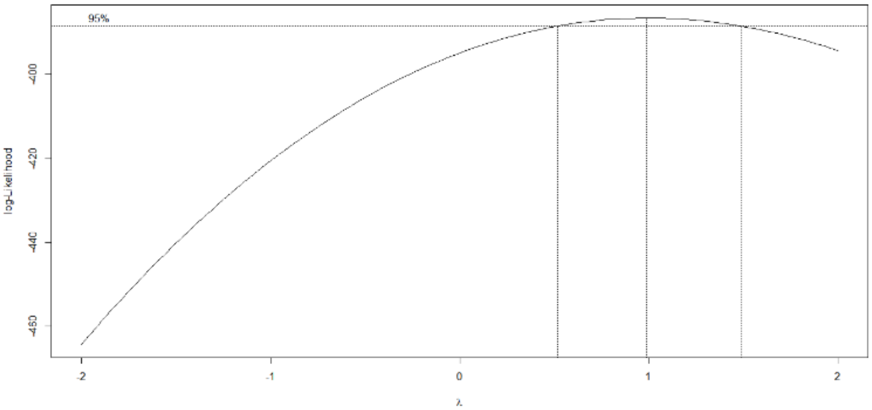

Figure 3. Transformed Data Plot
Source: Rstudio version 4.1.1

From Figure 3, it is shown that the lambda (λ) value is 1, which means the data is stationary in variance and no further transformation is required. Stationarity in the mean was then tested using the Augmented Dickey-Fuller test, with a p-value of 0.717. Since the p-value of 0.717 exceeds the 0.05 significance level, it implies that the time series is not stationary in terms of its mean, and thus, first differencing is required. After differencing, the ADF test produced a p-value of $0.01 < \alpha = 0.05$, confirming that the data is stationary in the mean. Once stationarity was achieved, the ARIMA model was selected based on observations of the ACF and PACF plots, as shown below.

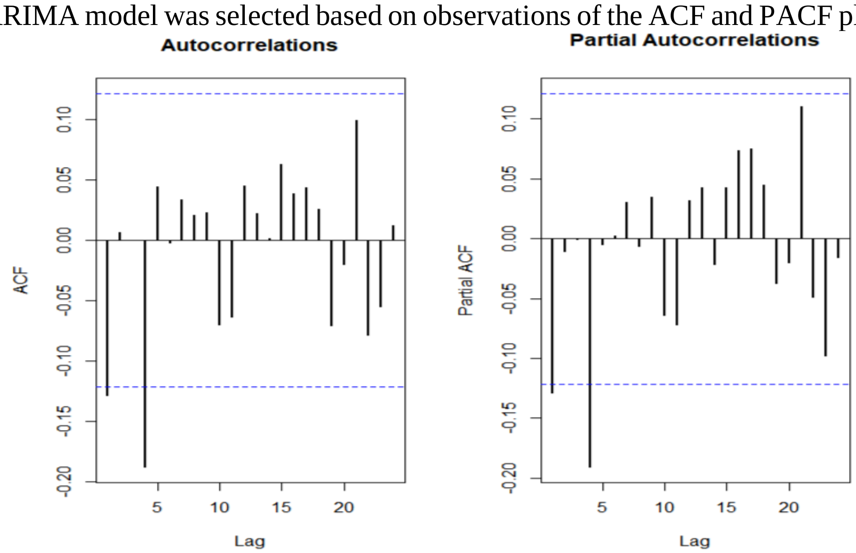

Figure 4. ACF and PACF
Source: Rstudio version 4.1.1

In Figure 4, the lags that exceed the threshold are lag 1 and 4. Therefore, the identified AR model is AR(1) and AR(4), and the identified MA model is MA(1) and MA(4). The obtained (p, d, q) models are (1,1,1), (1,1,4), (4,1,1), and (4,1,4). The table below presents the estimation results and AIC values for the ARIMA (p, d, q) models.

Table 1. ARIMA Model Selection ($\boldsymbol{p, d, q}$)

Model	Parameter	AIC
ARIMA (1,1,1)	Significant	17123.13
ARIMA (1,1,4)	Not Significant	17120.51
ARIMA (4,1,1)	Not Significant	17120.22
ARIMA (4,1,4)	Not Significant	17125.27

In Table 1, it is shown that ARIMA (1,1,1) is a significant model. Since the only considerable model is ARIMA (1,1,1), this model is selected as the best model, with an AIC value of 17123.13. Subsequently, diagnostic testing is performed to verify whether the model's residuals satisfy the assumption of white noise. As shown by the Ljung-Box test, the p-value stands at 0.699, greater than the significance level α = 0.05, indicating that the residuals are white noise, and therefore the model is valid for forecasting. The ARIMA (1,1,1) model is expressed as follows.

$$\phi_p(B)(1-B)^d A_t = \theta_0 + \theta_q(B)\alpha_t \quad (7)$$

$$(1 - 0.5586B)(1-B)A_t = (1-0.6749B)\alpha_t \quad (8)$$

$$(1 - 0.5586B - B + 0.5586B^2)A_t = (1\text{-}0.6749B)\alpha_t \quad (9)$$

$$(1 - 1.5586B + 0.5586B^2)A_t = (1-0.6749B)\alpha_t \quad (10)$$

$$A_t - 1.5586A_{t-1} + 0.5586A_{t-2} = \alpha_t - 0.6749\alpha_{t-1} \quad (11)$$

$$A_t = 1.5586A_{t-1} - 0.5586A_{t-2} + \alpha_t - 0.6749\alpha_{t-1} \quad (12)$$

The forecasting results for the ARIMA (1,1,1) model are shown in Table 2.

Table 2. ARIMA (1,1,1) Model Forecast Results

Forecast Result	Actual Data
5688	5750
5682	5850
5678	5775
5676	5825
5675	5850
5674	6025
5674	6000
5674	6125
5673	6150
5673	6100
5673	6300
5673	6300
5673	6250
5673	6125
5673	6175
5673	6125
5673	6225

Based on Table 2, the calculated MAPE value for the ARIMA (1,1,1) model is 6.203%, which indicates that the stock price of BRI tends to experience a significant decline.

Before proceeding with the Backpropagation Neural Network modeling, the residual data from the ARIMA (1,1,1) model is normalized. The residual data ranges from a minimum of -3358 to a maximum of 3543, resulting in the normalized values below.

$$A't = \frac{A - A_{min}}{A_{max} - A_{min}} \quad (13)$$

$$A'_1 = \frac{874-(-3358)}{3543-(-3358)} = 0.61324446 \quad (14)$$

Continuous calculations are performed until all data is normalized. The normalized data is then used as input for the Backpropagation Neural Network and the Conjugate Gradient Powell Beale algorithm. This study uses a sigmoid activation function and a learning rate of 0.01. The number of input units is identified through lag significance analysis in the PACF plot of ARIMA, where the significant lag is lag 4. Determining the number of hidden units involves a trial-and-error process that varies for each artificial neural network case, so training and testing are conducted for various numbers of hidden units [18]. This study performs a trial-and-error process from 1 to 10 units. The optimal network is determined based on the smallest RMSE value during training, using 1 input layer with 4 neurons, 1 hidden layer with 1 to 10 neurons, and 1 output layer with 1 neuron. The following are the results of the Backpropagation network training:

Table 3. Backpropagation Network Training Results

Hidden Unit	Actual Data
1	566.9890
2	482.8098
3	613.3141
4	**428.5028**
5	1245.4448
6	1232.8903
7	1630.2826
8	757.9953
9	1009.1540
10	893.5576

The training results presented in Table 3, which utilized one input layer containing 4 neurons, one hidden layer with the number of neurons ranging from 1 to 10 units, and one output layer with a single neuron, produced an optimal network architecture consisting of one input layer with 4 units, one hidden layer with 4 units, and one output layer with 1 unit. This network configuration is denoted as [4-4-1]. The training process took approximately 0.06 seconds, although the duration may fluctuate. Figure 5 presents the design of the [4-4-1] network architecture model.

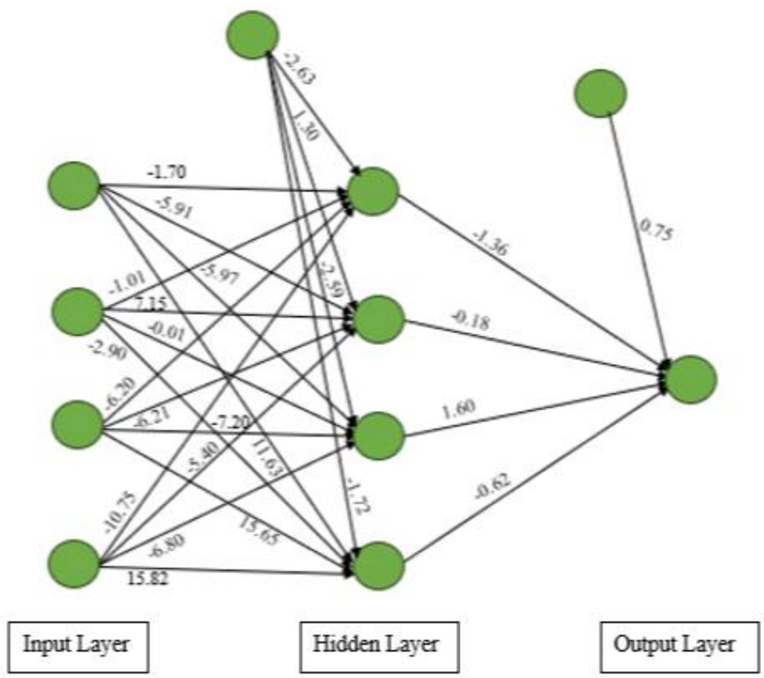

Figure 5. Architecture [4-4-1]
Source: Rstudio version 4.1.1

Below, Tables 4 and 5 show the weights that connect the neurons.

Table 4. Weights connecting each input unit to the hidden units.

Hidden Unit	Input Unit				
	Biased	1	2	3	4
1	-2.63	-1.70	-5.91	-5.97	11.63
2	1.30	-1.01	7.15	-0.01	-2.90
3	-2.59	-6.20	-6.21	-7.20	15.65
4	-1.72	-10.75	-5.40	-6.80	15.82

Table 5. The connection weights between each hidden neuron and the output neuron

Output Unit	Hidden Unit				
	Biased	1	2	3	4
1	0.75	-1.36	-0.18	1.60	-0.62

After obtaining the ARIMA (1,1,1) model and the Backpropagation Neural Network architecture [4-4-1], these models will be used for forecasting. Below are the forecasting results of the hybrid ARIMA-Backpropagation Neural Network:

Table 6. Hybrid Forecast Model Result

Forecast Result	Actual Data
6204	5750
6201	5850
6134	5775
5735	5825
6111	5850
6086	6025
6107	6000
5674	6125
6111	6150
6122	6100
6098	6300
6116	6300
6097	6250
6099	6125
6125	6175
6091	6125
6075	6225

Table 6 shows that the ARIMA (1,1,1)-Backpropagation Neural Network [4-4-1] model achieves a MAPE of 2.516%. The prediction results suggest that the model aligns well with the actual data.

Presented below is a plot comparing the forecast outcomes of ARIMA (1,1,1), the hybrid ARIMA (1,1,1)-Backpropagation Neural Network [4-4-1], and the actual data.

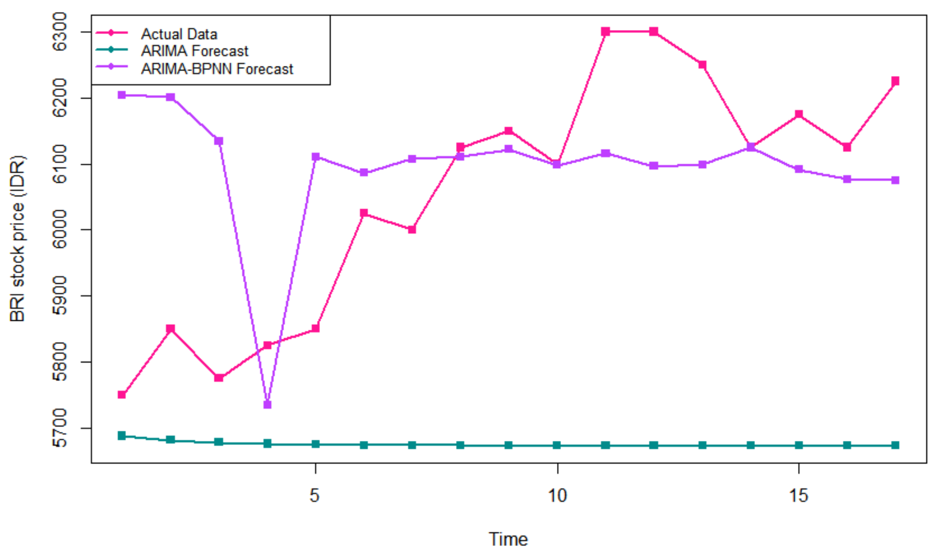

Figure 7. Plot Comparing Forecasted and Actual Values
Source: Rstudio version 4.1.1

Figure 7 shows that the ARIMA (1,1,1)-Backpropagation Neural Network [4-4-1] model is better at matching the actual data compared to the ARIMA (1,1,1) model. Next, the forecast accuracy for PT. Bank Rakyat Indonesia (Persero) Tbk's stock prices will be calculated to find the best model.

Table 8. Forecast Accuracy Results

Method	Model	MAPE	RMSE
ARIMA	ARIMA (1,1,1)	6.203%	421.5896
Hybrid ARIMA-BPNN	ARIMA (1,1,1)-BPNN [4-4-1]	2.516%	200.1592

The comparison results in Table 6 indicate that the hybrid ARIMA-Backpropagation Neural Network (BPNN) method yields lower MAPE and RMSE values than the ARIMA method alone. The hybrid ARIMA–BPNN method also achieves a smaller MAPE value when compared to several previous studies on the stock price forecasting of PT. Bank Rakyat Indonesia (Persero) Tbk. For instance, study [22], employed a Recurrent Neural Network to forecast BBRI stock prices and obtained an MAPE of 9.2348%. Study [23] used a Linear Regression algorithm as a stock trading strategy and reported a MAPE of 13.751% in predicting BRI stock prices. Additionally, study [24] compared the performance of ARIMA and hybrid ARIMA–GARCH models, reporting MAPE values of 2.256% for the ARIMA model and 21.735% for the ARIMA–GARCH model. These findings demonstrate that the hybrid ARIMA-Backpropagation Neural Network method has superior forecasting capability, achieving an MAPE of 2.516%, suggesting that the hybrid ARIMA–BPNN model is a more accurate approach for forecasting the stock prices of PT. Bank Rakyat Indonesia (Persero) Tbk.

3. CONLUSIONS

Based on the conducted analysis, the hybrid ARIMA-Backpropagation Neural Network model, namely ARIMA (1,1,1)-Backpropagation Neural Network [4-4-1], demonstrates superior accuracy, achieving a MAPE of 2.516% and an RMSE of 200.1592, compared to the standalone ARIMA (1,1,1) model with a MAPE of 6.203% and RMSE of 421.5896. This hybrid approach begins by using the ARIMA method to process the training data, continuing until the most suitable ARIMA model is determined. After obtaining the best ARIMA model, which is ARIMA (1,1,1), and the Backpropagation Neural Network architecture model [4-4-1], the two models are combined to generate hybrid predictions. Subsequently, the accuracy levels of both the ARIMA model and the hybrid ARIMA-Backpropagation Neural Network model are calculated. The results demonstrate that the hybrid ARIMA-Backpropagation Neural Network method is more effective for investors in predicting the stock price of PT. Bank Rakyat Indonesia (Persero) Tbk, as it provides higher accuracy.

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