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Forecasting the Stock Price of PT Aneka Tambang Tbk (ANTM) Using a Neural Network Approach

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ABSTRACT

Stock price prediction plays a significant role in supporting rational investment decision-making amidst the volatility of the Indonesian capital market. Accurately forecasting stock price movements, especially for leading stocks in the energy sector such as PT Aneka Tambang Tbk (ANTM), is crucial because these stocks play a key role in maintaining national economic stability. However, most previous research has been limited to linear models such as ARIMA, which are less able to capture non-linear and dynamic data patterns. This situation creates a research gap regarding the need for a more adaptive approach to the complexity of the stock market. To address this gap, this study offers a novel approach by applying an advanced machine learning approach based on Neural Networks (NN) to predict the stock price of PT Aneka Tambang Tbk (ANTM). The research data was obtained from the *Investing.com* website, covering the observation period from January 2020 to August 2025. The results showed that the Neural Network (NN) model was effective in predicting the weekly stock price of PT Aneka Tambang Tbk (ANTM), with the best performance achieved using the tanh activation function, an alpha value of 0.01, and a hidden layer architecture of 300;300. This model achieved high accuracy with an RMSE of 130.4853, an MAE of 91.5722, and a MAPE of 5.29%. These results indicate that the NN model successfully captures complex market patterns and provides accurate predictions, making it a valuable tool for investors and policymakers in making informed investment decisions.

Keyword: *ANTM, Forecasting, Machine Learning, Neural Network*

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1. Introduction

People who invest have expectations of making a profit, for example through capital gains, which represent the difference between the selling price and the purchase price (Haque et al., 2017). Before making investment decisions, investors also consider various important indicators such as a company's value (Sibrani et al., 2024). Companies with good corporate value tend to be more attractive to investors for capital investment (Sibrani et al., 2024). One category of investment that is in high demand is blue chip stocks, which are stocks from companies with good reputations, solid financial foundations, and reliable performance records (Nickolas, 2024). Lubis et al. (2024) state that blue chip stocks are owned by large companies with high assets and market capitalization, low debt levels, good returns, and relatively low market risk. Although there is no official definition of blue chip stocks, stocks categorized as blue chips in Indonesia usually have a market capitalization of at least IDR 10 trillion (Rafsanjani et al., 2025). Thus, the IDR 10 trillion threshold is widely used as a reference for categorizing blue chip stocks in the Indonesian capital market.

The selection of blue chip stocks in this study focused on one energy company that continues to be classified as a blue chip stock in Indonesia, namely Aneka Tambang Tbk (ANTM) (Wikanto & Virasma, 2025). Based on the latest data from Investing.com as of August 2025, ANTM has a market capitalization value of IDR 71.6 trillion. In 2023, ANTM stock ranked fourth as the largest nickel company in Indonesia (Leend, 2024). According to Santosa (2025), ANTM is the main gold producer in Indonesia. In addition, these shares regularly pay dividends and show fairly stable financial results despite facing fluctuations in global commodity prices. The movement of ANTM's share price affects the local capital market. For example, in early June 2025, when ANTM's share price declined, it was attributed to investor concerns about the suspension of operations of its subsidiary in Raja Ampat, which affected ANTM's market capitalization (Kurnia, 2025). These factors make ANTM stock an ideal representation for analysing investment opportunities in the energy sector through forecasting methods.

In order to understand the dynamics of the Indonesian capital market and its contribution to the achievement of the sustainable development agenda, research can be conducted in the form of stock price predictions for PT Aneka Tambang Tbk (ANTM). Research on PT Aneka Tambang Tbk shares has been conducted by Wardhani & Yudhanegara (2025), who applied the ARIMA (3,1,0) model to project ANTM's share price for the next four weeks, with a fairly good accuracy rate as indicated by a Mean Absolute Percentage Error (MAPE) value of 7.68%. The novelty of this study lies in its analysis of blue chip stocks in the energy sector, particularly PT Aneka Tambang Tbk (ANTM). In addition, this study applies the latest machine learning-based method, namely Neural Network (NN), to compare stock price prediction performance so as to assist in making investment decisions.

Neural Networks (NN) are machine learning models that mimic the way the brain works with layers of neurons. Multilayer Perceptron (MLP), which is a classic architecture in ANN, is quite efficient in recognizing nonlinear patterns in time series data. Although MLP has a simple architecture, it is still capable of providing high accuracy in forecasting and can recognize nonlinear relationships due to its nature as a universal approximator (Lazcano et al., 2024). There is a study comparing the ARIMA and Artificial Neural Network (ANN) models in forecasting the number of bull services by Rola et al. (2020) using quarterly data for the 2002-2017 period, which shows that ANN consistently outperforms ARIMA with a MAPE of 0.55%.

Based on the issues described above, this study is expected to make a significant contribution to the development of literature on stock price prediction, especially in the energy sector. This research is expected to not only benefit investors in determining more appropriate investment steps, but also support the achievement of Sustainable Development Goals (SDGs) point 8, namely Decent Work and Economic Growth, through increased economic stability. Therefore, the author believes that the use of the Neural Network (NN) method in this study will provide a new perspective as well as a practical contribution to sustainable economic development in Indonesia.

2. Literature Review

2.1 Partial Autocorrelation Function (PACF)

The PACF is a measure that describes the partial correlation between a time series variable and a specific lag, after the influence of other lags has been eliminated. This function is also used to identify lags that have an influence that will be used as predictor variables in forecasting models (Leites et al., 2024). According to Wei (2005), PACF at lag h can be defined as follows:

$$\phi_{hh} = Corr(Y_t, Y_{t-h} \mid Y_{t-1}, Y_{t-2}, \dots, Y_{t-h+1}) \tag{1}$$

where ϕ_{hh} is the bivariate correlation of Y_t and Y_{t-h} conditional on $Y_{t-1}, Y_{t-2}, \dots, Y_t$. In addition, the above equation can also be written in recursive form as follows:

$$\phi_{hh} = \frac{\rho_h - \sum_{m=1}^{h-1} \phi_{h-1,m}\rho_{h-m}}{1 - \sum_{m=1}^{h-1} \phi_{h-1,m}\rho_m} \tag{2}$$

2.2 Nonlinearity Test

Nonlinearity testing is a statistical method used to evaluate the existence of nonlinear relationships between certain variables. A number of methods have been developed to detect nonlinearity, one of which is the Terasvirta test. According to Prabowo et al. (2020), the Terasvirta test is one of the best methods for identifying nonlinearity in data. In general, models with nonlinear properties can be written as follows:

$$y_t = \varphi(\boldsymbol{\delta}'\boldsymbol{z_t}) + \boldsymbol{\alpha}'\boldsymbol{z_t} + \varepsilon_t;\ \ \varepsilon_t \sim IIDN(0, \sigma^2) \tag{3}$$

where $\boldsymbol{\alpha} = (\alpha_0, \dots, \alpha_p)'$ is the weight vector for the linear component, $\boldsymbol{z_t} = (1, y_{t-1}, \dots, y_{t-p})'$ is a vector consisting of constants and lags of the variable y_t, $\boldsymbol{\delta}' = (\delta_0, \widetilde{\boldsymbol{\delta}}')$ is a vector of weight parameters for nonlinear components with $\widetilde{\boldsymbol{\delta}}' = (\delta_1, \dots, \delta_p)$, and the function $\varphi(\boldsymbol{\delta}'\boldsymbol{z_t})$ as the sigmoid weight activation function that maps the nonlinear relationship in the model.

Accordingly, the hypotheses applied in the Terasvirta test can be stated as follows:

H_0 : $\lambda_{01}, \dots, \lambda_{0q} = 0$ (data follows a linear pattern)

H_1 : setidaknya terdapat satu $\lambda_{0q} \neq 0$ (data follows a nonlinear pattern)

The critical region for rejecting H_0 is determined when the value of $F_{hitung} > F(\alpha; m; n-p-m-1)$ or when the $p-value < \alpha$ with $\alpha = 5\%$.

2.3 Data Normalization

Data normalization is an important step in the preprocessing process to ensure that each feature is on a comparable scale. One widely used method is min–max normalization or min–max scaling, which is a technique that maps the original values to a specific range, generally [0,1] or [−1,1]. In this study, the new range was set between 0.1 and 1 to avoid zero values. The normalization equation used can be written as follows (Sinsomboonthong, 2022):

$$y'_t = \frac{y_t - min(data)}{max(data) - min(data)}\left(new_{max(data)} - new_{min(data)}\right) + new_{min(data)} \tag{4}$$

with,

y'_t : normalized data at time t

y_t : unnormalized data at time t

2.4 Neural Network (NN)

Neural Networks (NN) are a computational approach inspired by the way the human brain processes information (Pham et al., 2023). NN consists of a set of simple units called artificial neurons, where each neuron receives input, performs calculations through an activation function, and produces output that can be forwarded to the next neuron (Aftabi et al., 2024). In NN, there is a term called architecture, which consists of modeling layers, namely the input layer, hidden layer, and output layer. In the field of time series, the input used is the lag from the previous observation with the output being the forecast result. The equation used to obtain the output from the NN architecture is as follows:

$$\hat{Y}_t = f^{\circ}\left\{w_0 + \sum_{k=1}^{p}\left(w_k f^h\left(\sum_{i=1}^{n} b_{ik} x_{i,t}\right)\right)\right\} \quad (5)$$

where w_k refers to the weight linking the k-th hidden neuron to the ouput layer, while b_{ik} denotes the weight connecting the i-th input to the k-th neuron in the hidden layer. The activation functions applied in the hidden layer and the output layer arse represented by as $f^h(\blacksquare)$ and $f^{\circ}(\blacksquare)$, respectively.

The structure of the Neural Network model is presented in Figure 1 as follows:

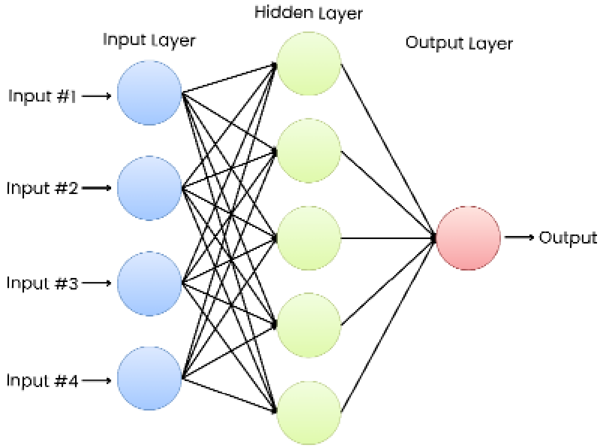

Figure 1. Neural Network Structure

In the NN structure shown in Figure 1, the hidden layer functions as a feature extraction stage. This layer is where the activation function is applied and weighted values are assigned. This neural network applies the backpropagation algorithm to repeatedly adjust its weights, aiming to reduce the discrepancy between the model's predictions and the actual target values.

2.5 Neural Network Activation Function

In Neural Network (NN) architecture, activation functions play a very important role. In general, non-linear activation functions are used to enable the network to model complex relationships. If activation functions are not applied, the relationship between input and output will be purely linear, causing the network to lose its ability to capture non-linear patterns that often appear in high-dimensional data. Therefore, activation functions serve to extract complexity from input data so that the network can produce more representative and accurate outputs. Several types of activation functions commonly used in NN architecture are presented in Table 1 as follows (Aftabi et al., 2024):

Table 1. Types of Activation Functions in NN

Types of Activation Functions	Formula
Tanh	$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$
Logistic (*Sigmoid/Soft Step*)	$f(x) = \frac{1}{1+e^{-x}}$
Rectified Linier Unit (*ReLU*)	$f(x) = \max\{x, 0\} = \begin{cases} x, if\ x \geq 0 \\ 0, if\ x < 0 \end{cases}$

2.6 Grid Search Optimization

In analysis using Neural Networks (NN), model parameter selection is a very important aspect. Incorrect parameters can cause the model to overfit or underfit, thereby reducing prediction accuracy. Therefore, an optimization procedure is needed to find the most optimal combination of parameters so that the model can produce accurate predictions and have good generalization. One approach that is widely used to determine optimal parameters is Grid Search Optimization (GSO). GSO is a systematic search method that tests all combinations of parameter values in a predetermined search space (Bakal et al., 2022). To evaluate the parameter search results, a walk-forward validation approach is used. This method maintains the temporal order by dividing the time series data into n-training sets and n-testing sets. In time series data, the combination of GSO and walk-forward validation is the most appropriate approach because it maintains the consistency of the time sequence while producing a prediction model with high reliability. The parameter value tuning are displayed in Table 2 below:

Table 2. Parameter Tuning in NN Models

Algorithm	**Parameter Tuning**
Neural Network (NN)	*Activation Function* : [*Tanh, Logistic, ReLU*] *Alpha* : [0,0001; 0,001; 0,01] *Hidden Layer Size* : [50, 100, 150, 200, 250, 300, 50:50, 100:100, 150:150, 200:200, 250:250, 300:300]

2.7 Model Goodness Test

The formula for calculating the three goodness-of-fit values is as follows:

1. Root Mean Squared Error (RMSE)
   Equation (6) shows the computation of RMSE and is expressed as follows (Hodson, 2022):

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \tag{6}$$

where y_t represents the actual data, $\hat{y}_t$ denotes the forecast value, and n is the amount of data.

2. Mean Absolute Error (MAE)
   Equation (7) shows the computation of MAE and is expressed as follows (Yang & Mao, 2023):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \tag{7}$$

where y_t represents the actual data, $\hat{y}_t$ denotes the forecasted value, and n is the amount of data.

3. Mean Absolute Percentage Error (MAPE)
   Equation (8) shows the computation of MAPE and is expressed as follows (Hung et al., 2022):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{(y_t - \hat{y}_t)}{y_t}\right| \times 100\% \tag{8}$$

where y_t represents the actual data, $\hat{y}_t$ denotes the forecasted value, and n is the amount of data. According to Mahsup et al. (2024), MAPE also has a class categorization that can be used to assess the accuracy level of a prediction model. The categories are as follows:

Table 3. MAPE Value Categories

MAPE Value	**Category**
$MAPE < 10\%$	Very Accurate
$10\% \le MAPE < 20\%$	Accurate
$20\% \le MAPE < 50\%$	Fairly Accurate
$MAPE \ge 50\%$	Not Accurate

3. Research Methods

3.1 Data and Data Sources

The data used in this study is weekly stock price data for PT Aneka Tambang Tbk. (ANTM) obtained from the Investing.com website, which is commonly used for stock price monitoring. The period used in this study ranges from January 2020 to August 2025. In this research, the dataset is partitioned into training and testing subsets using a 70:30 ratio. With a collection of 289 weekly data points, there are 202 data points for training covering the period from January 5, 2020 to November 19, 2023, while the other 87 data points are for testing covering the period from November 26, 2023 to August 3, 2025.

3.2 Data Analysis Steps

The data analysis steps performed are described in detail as follows:

1. Descriptive Analysis of ANTM Stock
   Presenting data visualization in the form of a time series plot (line chart) to illustrate weekly share price movements, as well as describing data characteristics and trends through descriptive statistical analysis.
2. Training Data Analysis
   a. Determining significant lag using PACF analysis according to Equation (1)
   b. Performing Terasvirta tests to identify nonlinear relationships between variables.
   c. Performing data normalization based on Equation (4) so that all variables are on the same scale.
   d. Converting data into time lag form as input for the Neural Network model
3. Neural Network Model Analysis
   Designing the Neural Network architecture by determining the number of hidden layers, activation functions, and alpha using the backpropagation algorithm.
4. Model Training and Testing
   Training the model with training data and predicting stock prices using testing data.
5. Model Performance Evaluation
   Evaluate prediction results using the RMSE metric based on Equation (6), MAE based on Equation (7), and MAPE based on Equation (8) to assess the model's accuracy level.

4. Results and Discussion

4.1 Descriptive Statistics

Based on ANTM stock value data sourced from Investing.com, 289 weekly data points were obtained covering the period from January 5, 2020 to August 3, 2025. The data was then split into training and testing sets. The training set covers the period from January 5, 2020 to November 19, 2023, and a summary of this data is shown in Table 4 below

Table 4. Descriptive Statistics of Training Data

Variable	Mean	Standard Deviation	Minimum	Maximum
ANTM stock	1827.5	679.8	374	3120

Based on Table 4, the share price of ANTM has an average of IDR 1,827.5 with a standard deviation of IDR 679.8, indicating significant price fluctuations. The lowest value of IDR 374 occurred on March 15, 2020, when the COVID-19 pandemic triggered market instability and a decline in commodity prices. Meanwhile, the highest value of Rp3,120 on January 10, 2021 occurred due to increases in nickel and gold prices and market optimism regarding the transition to energy and electric vehicles, which drove an increase in nickel demand. The ANTM stock time series plot with a 70% training period and 30% testing period is presented in Figure 2 as follows:

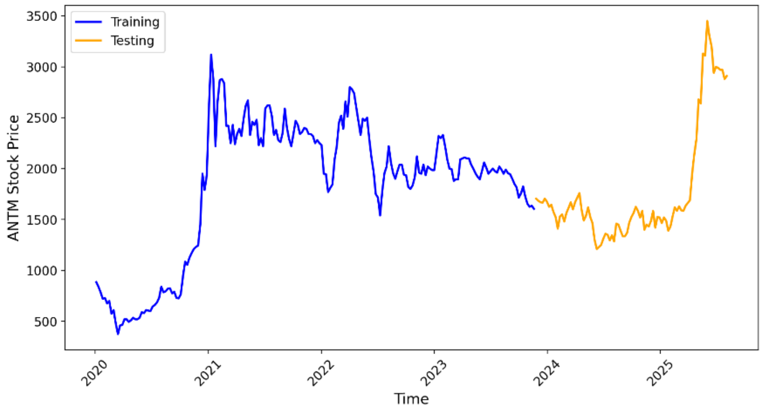

Figure 2. ANTM Stock Time Series Plot

4.1 Determining Input Lag

In time series analysis, determining input lag plays an important role in identifying significant lags that will be used as predictor variables. This stage is carried out by looking at the PACF plot, which describes the partial correlation between variables in a time series. The results of the PACF plot analysis showing significant lags are displayed in Figure 3 as follows.

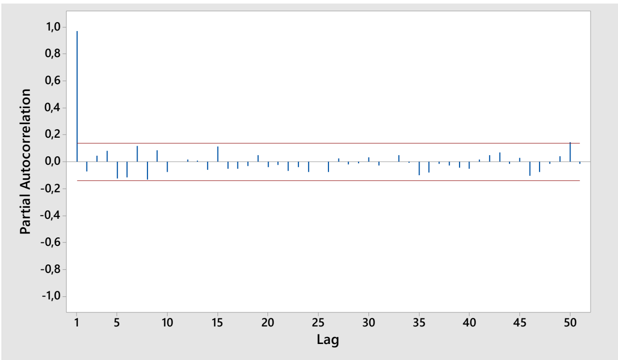

Figure 3. ANTM Stock PACF Plot

Figure 3 shows the PACF plot for ANTM stock, where only lag 1 appears to have a significant effect on ANTM stock. Therefore, in modeling ANTM stock, the division of y_t data begins at period $t = 1$ so that all significant lags can be used as predictor variables in the model.

4.1 Nonlinearity Testing

The next step after obtaining significant lag is to determine the data pattern that will be used as a reference in setting several model parameters, such as selecting the type of activation function in the Neural Network (NN) model. This data pattern identification stage is carried out through the Terasvirta test, which aims to determine whether the data characteristics are linear or non-linear. The results of the non-linearity test for ANTM stock are shown in Table 5 as follows:

Table 5. Nonlinear Test Results

Lag	Test Statistics	P-Value
1	7.7003	0.0006

Based on the Terasvirta test presented in Table 5, it is known that for ANTM stocl at lag 1, the p-value obtained is smaller than the significance level $\alpha = 5\%$. This indicates that H_0 is rejected, so it can be concluded that the ANTM stock data shows a non-linear relationship pattern. Thus, in the modeling stage using NN, it is necessary to select an activation function that is capable of handling the complexity of non-linear relationships between variables. Suitable activation functions include Tanh, Logistic, and Rectified Linear Unit (ReLU).

4.1 Neural Network Modeling and Prediction

The selection of the NN model was based on the results of the Terasvirta test, which showed that the data had non-linear characteristics. Therefore, several types of activation functions were used, such as Tanh, Logistic, and Rectified Linear Unit (ReLU). Before the modeling process was carried out using the grid search and walking forward validation approaches, the data first underwent normalization using the formula shown in Equation (4). Next, the process of searching for the best parameter combination was carried out based on the initial parameter values specified in Table 2. The results of the optimization process produced optimal parameters for neural network modeling on ANTM stock, which are shown in detail in Table 6 below:

Table 6. Optimal NN Parameters

Activation Function	Parameter	Optimal Value
Tanh	Alpha	0.01
	Hidden layer size	300;300
Logistic	Alpha	0.0001
	Hidden layer size	200;
ReLU	Alpha	0.01
	Hidden layer size	300;300

The performance of the neural network model predictions for ANTM stock using various activation functions is presented in Table 7 below:

Table 7. Comparison of NN Activation Function Performance

Activation Function	Parameter	Optimal Value
Tanh	RMSE	130.4853
	MAE	91.5722
	MAPE	5.29%
Logistic	RMSE	660.4062
	MAE	402.9457
	MAPE	17.64%
ReLU	RMSE	167.4466
	MAE	111.8575
	MAPE	5.64%

Table 7 shows a comparison of the performance of each NN activation function for ANTM stock data. Based on these results, the model with the tanh activation function provides the most optimal performance compared to other activation functions. The best parameters obtained in this model are alpha of 0.01 with a hidden layer size of 300;300. This optimal performance is reflected in the RMSE value of 130.4853, MAE of 91.5722, and MAPE of 5.29%, which indicates a relatively smaller prediction error rate compared to models with other activation functions. Then, the neural network model architecture with optimal parameters is shown in Figure 4 as follows:

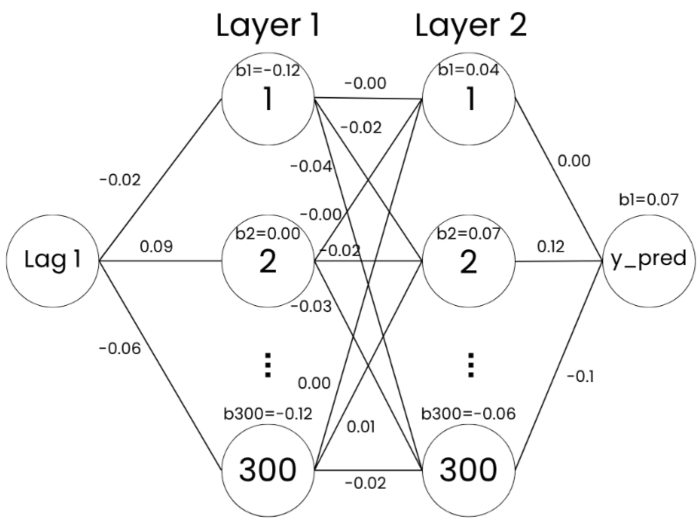

Figure 4. ANTM Stock Neural Network Structure

The results of forecasting on ANTM stock testing data using the NN method are presented in Figure 5 as follows:

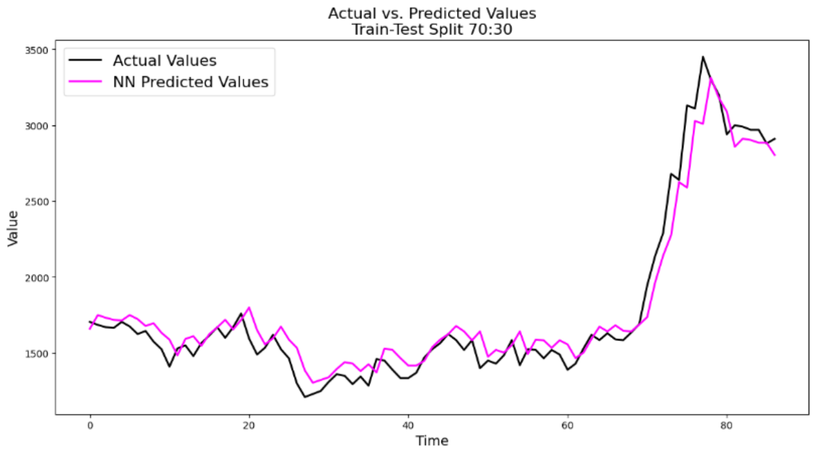

Figure 5. ANTM Stock Forecast Plot

Based on Figure 5, which shows the ANTM stock prediction plot, it can be seen that the NN model prediction pattern is able to follow the actual stock price movement trend quite well, especially during the sharp increase period towards the end of the data. Although there are slight differences at several points, especially during the rapid price fluctuation phase, in general the model successfully captures the direction and pattern of stock price changes consistently. This indicates that the Neural Network model has good generalization capabilities in predicting ANTM stock price movements based on the historical data used.

5. Conclusion

Based on the results of the above study, it shows that the Neural Network (NN) model is capable of effectively predicting the weekly stock price of ANTM, with test results showing that the data has a non-linear pattern, making the NN method the appropriate approach. The best model with the tanh function, alpha 0.01, and a hidden layer architecture of 300;300 is capable of producing a high level of accuracy with an RMSE of 130.4853, MAE of 91.5722, and MAPE of 5.29%. These results confirm that the NN model is capable of capturing complex market fluctuation patterns and providing reliable predictions, especially during periods of high volatility such as the COVID-19 pandemic and global commodity price increases. Thus, the application of NN is an important strategy for investors, analysts, and policymakers in making more accurate stock price predictions and supporting data-driven investment decisions amid uncertain market dynamics.

6. Declaration of AI and AI assisted technologies in the writing process

The authors utilized various artificial intelligence (AI) tools to improve the quality and accuracy of their manuscripts. Specifically, DeepL was used to facilitate translation between Indonesian and English; Grammarly was used to rephrase, improve language, and correct grammar; and Mendeley Reference Manager was used to organize citations and reference formats. All results generated or recommended by these tools have been thoroughly checked, edited, and verified by the authors. The authors are fully responsible for the content of this manuscript.

7. CRediT Authorship Contribution Statement

Author contributions (CRediT): Larisa Mutiara Putri—Conceptualization; Data curation; Formal analysis; Visualization; Writing – original draft; Writing – review & editing. M. Fariz Fadillah Mardianto—Conceptualization; Methodology; Supervision; Validation; Writing – review & editing. Elly Pusporani—Conceptualization; Methodology; Data curation; Validation; Project administration. Dita Amelia— Data curation ;Validation.

8. Declaration of Competing Interest

The authors state that no competing interests are involved.

9. Acknowledgments

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10. Data Availability

The data used in this study were obtained from the official website of Investing.com and are publicly available.

11. Funding

This study did not receive any external financial support.

12. Ethical Approval

Ethical clearance was unnecessary for this study, as it did not include human participants, animal experimentation, or the use of personal or sensitive information.

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