

COMPARATIVE EVALUATION OF ARIMA AND GRU MODELS IN PREDICTING RUPIAH DOLLAR EXCHANGE RATE

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Abstract: This study evaluates the effectiveness of the ARIMA (Autoregressive Integrated Moving Average) and GRU (Gated Recurrent Unit) models in forecasting the USD–Rupiah exchange rate. Exchange rate fluctuations influence overall economic stability, making accurate forecasting crucial. Monthly data from January 2001 to March 2024 were analyzed. The ARIMA model, a traditional statistical approach, combines autoregressive (AR), differencing (I), and moving average (MA) components to capture linear patterns, while the GRU model, a deep learning approach, captures nonlinear and complex temporal relationships using update and reset gate mechanisms to retain long-term information. Model performance was evaluated using the Mean Absolute Percentage Error (MAPE). The GRU model achieved a MAPE of 1.74%, lower than the ARIMA model's 1.94%, and generated a forecast of Rp. 16,399.91 for April 2024, closer to the actual value of Rp. 16,249.00 compared to ARIMA's Rp. 15,857.68. The findings demonstrate the GRU model's superior forecasting performance and provide empirical evidence of its effectiveness in modeling volatile exchange rate data, particularly the Rupiah–USD rate.

1. INTRODUCTION

Time series forecasting plays an important role in various fields, particularly in economics, finance, and policy planning, as it provides valuable insights for anticipating future trends. In recent years, time series forecasting has become increasingly significant in addressing fluctuations and uncertainties in financial markets. Forecasting involves using historical data to predict future values (Hyndman & Athanasopoulos, 2018). The forecasting method used will be adjusted to the needs and type of forecasting to be carried out (Wu et al., 2016). Optimal forecasting results can be achieved when the selected forecasting method is in accordance with the characteristics and conditions of the observed data. However, achieving accurate forecasts in practice is often challenging due to data volatility, seasonality, and nonlinear patterns that frequently appear in economic and financial data. Therefore, selecting an appropriate model that can adapt to complex data behavior is essential to produce reliable forecasting results that can support effective decision-making.

There are several methods that can be used in forecasting analysis, including the Autoregressive Integrated Moving Average (ARIMA) model. The ARIMA model requires certain assumptions such as stationarity and linearity, which may limit its applicability in complex data contexts (Kontopoulou et al., 2023). ARIMA is a quantitative technique frequently employed to predict future data by analyzing past data patterns. However, its effectiveness diminishes when the data does not meet the assumption of homogeneity of variance, a common issue in financial data such as currency exchange rates (Meilania et al., 2024). In Indonesia, fluctuations in the Rupiah and US Dollar exchange rate significantly affect economic stability. The high volatility of the exchange rate shows that traditional models such as ARIMA are less effective in capturing nonlinear and dynamic patterns. Therefore, more adaptive approaches like deep learning are required to enhance forecasting accuracy.

One of the major advances in time series forecasting is the adoption of deep learning methods, which are capable of modeling both linear and nonlinear patterns through multiple hidden layers. According to Lim & Zohren (2021), deep learning techniques demonstrate superior performance compared to traditional forecasting models by effectively capturing complex temporal dependencies within the data. Popular deep learning methods are Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) which have similar architectures. However, LSTM is more complex and has many parameters compared to GRU which has faster and easier computation because it only has two gates, namely reset gate and update gate (Wüthrich & Merz, 2023). Although simpler, GRU can still achieve comparable accuracy and is efficient in handling the problem of vanishing gradients (Chung et al., 2014). The GRU model is one of the latest methods in neural networks that has the ability to understand complex patterns in time series data. This model is capable of addressing time series forecasting challenges that involve intricate and non-linear patterns. This study focuses on forecasting the volatility of the Rupiah and US Dollar exchange rate, which has experienced significant fluctuations in recent years. It compares the ARIMA and GRU models to overcome the limitations of traditional methods in capturing nonlinear and dynamic financial time series patterns. This study focuses on forecasting the volatility of the Rupiah and US Dollar exchange rate, which has experienced significant fluctuations in recent years. It compares the ARIMA and GRU models to overcome the limitations of traditional methods in capturing nonlinear and dynamic financial time series patterns.

According to research conducted by Maharani et al. (2023). Forecasting the selling rate of the United States Dollar (USD) against the Rupiah (IDR) is important in many economic, trade and financial contexts. Currency exchange rates are one of the important indicators used to measure the economic health of a country, as well as to make informed investment and trade decisions. Ongoing fluctuations in exchange rates can be driven by macroeconomic factors like inflation and money supply. In addition, current exchange rate movements can also be influenced by previous exchange rates. According to (Nurpiah, 2022) USD as the most widely used currency for international transactions has a great influence on the currencies of other countries in the world, including the rupiah currency.

Based on several previous researchers, research conducted by Gustiansyah et al., (2023) which an analysis of the ARIMA model's application in forecasting world gold price data from 2010 to 2022 identified ARIMA (0,1,1) as the optimal model, based on AIC and MAPE values of 1264.731 and 11.972%, respectively. The forecast predicts an upward trend in world gold prices over the next six periods. In addition, in research conducted by (Ridwan et al., 2023), namely comparing ARIMA and GRU using stock price data of HIMBARA member banks, showing GRU is better than the ARIMA model. This conclusion is supported

by a comparison of MAPE values, where GRU provides a lower MAPE value compared to ARIMA. Similarly, (Zhong et al., 2023) compared both models for stock price forecasting and found that GRU produced more accurate results, especially for volatile data, demonstrating its superiority in capturing complex time series patterns.

Therefore, based on previous research, this study aims to compare the performance of the ARIMA and GRU methods in building the best model for forecasting the USD and Rupiah exchange rate using Mean Absolute Percentage Error (MAPE). This comparison is important because ARIMA effectively models linear and stationary data, while GRU can capture nonlinear and dynamic relationships. In addition, this study provides new evidence by applying both models to long-term exchange rate data in the Indonesian context.

2. LITERATURE REVIEW

2.1. Time Series Model

Forecasting in time series analysis refers to the process of predicting future values by identifying and modeling patterns and trends observed in historical data (Hyndman & Athanasopoulos, 2021). One of the most important assumptions in time series data is the assumption of stationarity, a time series is said to be stationary if there is no increasing or decreasing trend in the data long enough (Box et al., 2015). A stationary time series is characterized by a constant mean and variance over time, indicating that its statistical properties remain stable without systematic trends or seasonal effects (Hyndman & Athanasopoulos, 2021).

2.2. Autoregressive Moving Average (ARIMA)

In 1976, Box and Jenkins introduced the ARIMA model, which includes an autoregressive (AR) component of order p , a moving average (MA) component of order q , or a combination of both. For nonstationary time series data, a differencing process of order d is applied. The AR and MA aspects of the ARIMA model require that the data be stationary (Montgomery et al., 2015). A series is said to follow an ARIMA(p,d,q) process if it has the form of an equation:

$$Y_t = (1 + \phi_1)Y_{t-1} + (\phi_2 - \phi_1)Y_{t-2} + \dots + (\phi_p - \phi_{p-1})Y_{t-p} - \phi_p Y_{t-p-1} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q} \quad (1)$$

with ϕ and θ are parameters of autoregressive (AR) and moving average (MA) that are stationary, and ε_t is white noise. The ARIMA model parameters were estimated using the Maximum Likelihood Estimation (MLE) method.

2.3. Gated Recurrent Unit (GRU)

The Gated Recurrent Unit (GRU) is a form of recurrent neural network (RNN) that was introduced by Chung and colleagues in 2014. This model is a more streamlined version of the Long Short-Term Memory (LSTM) network, offering better performance with shorter training times. GRUs were designed to address the gradient problem by incorporating an update gate and a reset gate, as illustrated in Figure 1 (Ridwan et al., 2023).

Figure 1 is an image of GRU. The GRU forecasting process begins by inputting historical data (x_t), which passes through the update (z_t) and reset (r_t) gates to control how past information is retained or forgotten. A candidate hidden state (h'_t) is then generated and combined with the previous hidden state (h_{t-1}) to produce the updated hidden state (h_t). This process continues sequentially to learn temporal patterns and generate predictions for future periods.

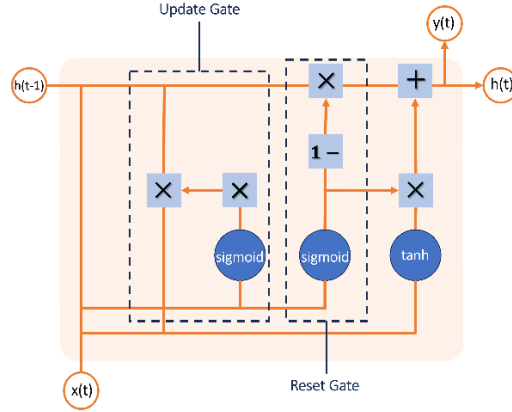


Figure 1. Gated Recurrent Unit Architecture

In modeling, the initial stage is to calculate the update gate (z_t) at this stage, it is used to help the model determine how much past information will be applied to the next process with the following formula:

$$z_t = \sigma(w^{(t)}x_t + u^{(t)}h_{t-1} + b) \quad (2)$$

In this context, w and u represent weights, x_t denotes the input at time t , h_{t-1} stands for the hidden state, and b signifies the bias. The subsequent step involves computing the reset gate (r_t), which determines the extent to which previous information should be discarded and how to integrate the new input with the existing information. This process is governed by the following equation:

$$r_t = \sigma(w^{(r)}x_t + u^{(r)}h_{t-1} + b) \quad (3)$$

Next, compute the hidden state h'_t , which the reset gate will use to preserve essential information from previous steps, using the following equation:

$$h'_t = \tanh(wx_t + r_t \odot uh_{t-1}) \quad (4)$$

The operation denoted by $\odot$ is known as the Hadamard product, which involves element-wise multiplication of two matrices of the same dimensions.

The last stage is to calculate the hidden state (h_t) which will produce the output (y_t) with the following formula:

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot h'_t \quad (5)$$

where h_t denotes the hidden state at time step t , h_{t-1} is the hidden state from the previous time step, h'_t represents the candidate hidden state computed from the current input z_t is the update gate that determines how much past information is retained.

The GRU model parameters, including weights (W), biases (b), and hidden units, are initialized randomly and optimized during training using the Adam optimizer through backpropagation to minimize the loss function. The performance of the GRU model depends on several hyperparameters, including dropout, validation split, number of neurons, learning rate, and epochs. Dropout and validation split help prevent overfitting, while the number of neurons, learning rate, and epochs control the model's learning capacity and convergence speed.

2.4. Exchange Rate

An exchange rate is a comparison of values or prices between two different currencies (Triyono, 2008). Fluctuations in the demand and supply of a foreign currency can lead to either appreciation or depreciation of the exchange rate. For instance, if the demand for the

currency rises while the supply stays unchanged, the exchange rate is likely to appreciate. On the other hand, if the supply of the currency increases while the demand remains steady, the exchange rate tends to depreciate.

3. MATERIAL AND METHOD

3.1. Data Source

The data used in the model estimation process is monthly data on the USD exchange rate against the rupiah from January 2001 to March 2024. Monthly data were used to reduce short-term fluctuations and random noise that often occur in daily exchange rate data. This aggregation allows the model to capture long-term trends and general patterns more effectively, providing stable and interpretable forecasting results. The total data is 279, data available on the website of the Ministry of Trade, www.kemendag.go.id.

3.2. Data Analysis

This research compares the performance results of two methods, namely ARIMA and GRU in forecasting the rupiah exchange rate against the USD. Figure 2 shows The flow of the research stages.

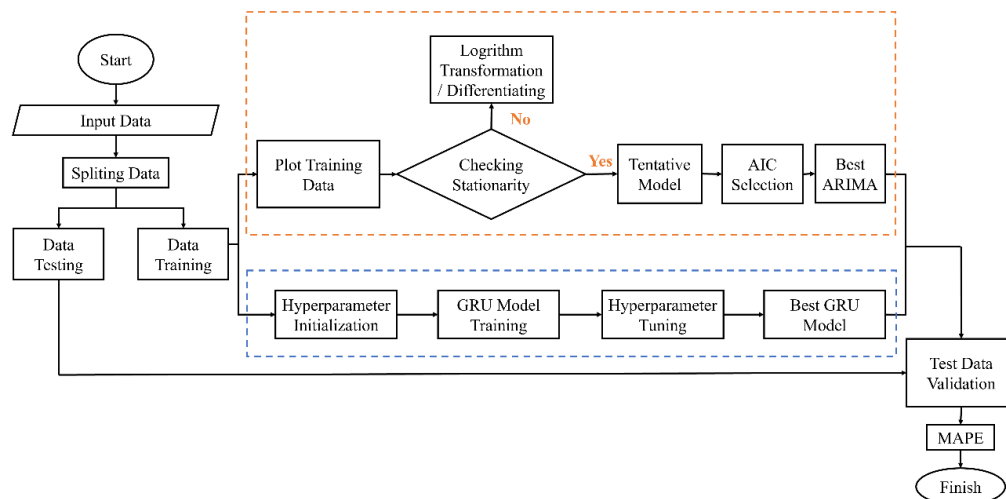


Figure 2. Research Stages

In Figure 2, the research process begins with data input and preprocessing to ensure data quality and consistency. The data are then divided into training and testing sets. The training data are used to build the ARIMA and GRU models, where ARIMA parameters (p, d, q) are determined based on the AIC, and GRU parameters are optimized using the Adam optimizer. The test data are used for model validation, and the forecasting accuracy of both models is evaluated using the Mean Absolute Percentage Error (MAPE) to determine the best-performing method.

3.3. Model Accuracy

A critical step in forecasting is assessing the accuracy of the predictions. This study utilizes MAPE (Mean Absolute Percentage Error) to gauge forecast accuracy. The formula for calculating MAPE is as follows:

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{e_t}{y_t} \right| \times 100 \quad (6)$$

in this study y_t denotes the real data value at the time t.

4. RESULTS AND DISCUSSION

Descriptive statistical analysis was conducted to provide an overview of the rupiah exchange rate against the USD during the observation period from January 2001 to March 2024. The results are presented in Table 1.

Table 1. Descriptive Statistics of Rupiah Exchange Rate Against USD (2001–2024)

Statistic	Value (IDR)
Minimum	8,279.00
Maximum	16,367.00
Mean	11,468.41
Median	10,430.00
Standard Deviation	2,432.40

The exchange rate ranged from IDR 8,279 to IDR 16,367 per USD, with an average value of IDR 11,468.41. The median exchange rate was IDR 10,430, and the standard deviation of IDR 2,432.40 indicates moderate fluctuations in the exchange rate throughout the study period.

Before selecting the best forecasting model, the dataset was divided into two subsets: training data and test data. The training data, consisting of 80% of the total observations (223 data points), were used to build and estimate the parameters of each model. The remaining 20% (56 data points) were used as test data to evaluate and validate the forecasting accuracy of the models.

The ACF and PACF graphs are the first step needed to check the stationarity of the data. By looking at the ACF and PACF graphs we can determine whether the data is stationary or not. The ACF and PACF graphs can be seen in Figure 3.

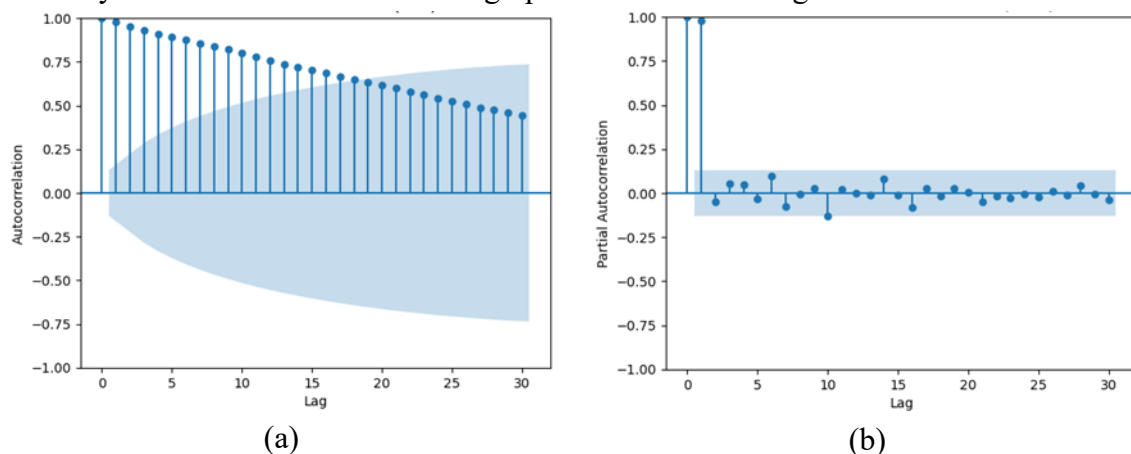


Figure 3. Plot Before Stationary: (a) ACF; (b) PACF

From Figure 5 it can be seen that the data is not yet stationary, on the ACF graph the lag drops slowly which means it can be concluded that the data is not yet stationary. In addition, to be more convincing, the Augmented Dickey-Fuller (ADF) test is carried out, the p-value is 0.923, which means the p-value > 0.05. So, it can be concluded that there is not enough evidence to state that the time series is stationary.

Non-stationary data can be converted to stationary by differencing. In this study, differencing is done once and the data already looks stationary. After differencing, there is no trend which means the data is stationary to the mean. Furthermore, it can be seen from the ACF and PACF plots in Figure 4.

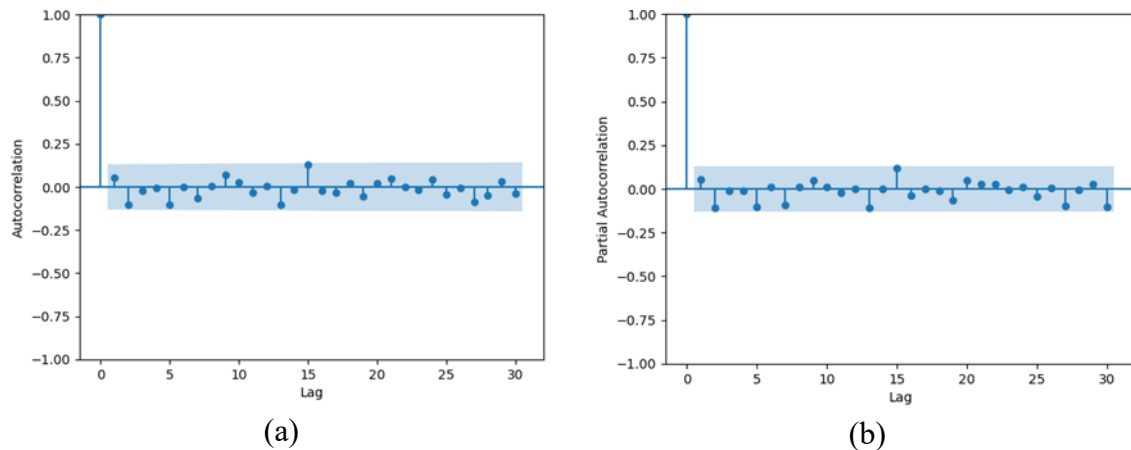


Figure 4. Stationary Plots: (a) ACF; (b) PACF

One of the popular metrics used to select the optimal model is AIC, by looking at the model that has the lowest AIC value we can determine the best model. Table 2 provides information on some tentative models and their AIC values.

Figure 4 shows that there are no significant lags, indicating that the data is stationary. There is no significant autocorrelation pattern in this data, indicating that the data values are independent of time and the fluctuations are random with no clear seasonal pattern or trend. The ADF test was conducted again to be sure and the result was 6.50×10^{-9} which is enough evidence to say that the data is stationary.

Table 2. AIC Value of the Tentative Model

Model	Nilai AIC
ARIMA (1,1,1)	3228.836
ARIMA (0,1,0)	3361.126
ARIMA (1,1,0)	3320.318
ARIMA (0,1,1)	3227.538

Based on the data Table 2, the ARIMA (0,1,1) model is identified as the best model, having the lowest AIC value of 3227.538. Subsequently, an overfitting process was performed with the ARIMA (1,1,1) and ARIMA (0,1,2) models. The results indicate that the tentative ARIMA (0,1,1) model maintains the smallest AIC value of 3227.538, compared to the ARIMA (1,1,1) model with an AIC value of 3228.836 and the ARIMA (0,1,2) model with an AIC value of 3228.661. Additionally, the other two models produced several insignificant parameter values and higher MAPE values than the ARIMA (0,1,1), as shown in Table 3.

Table 3. MAPE Value for ARIMA Model

Model	Nilai AIC
ARIMA (0,1,1)	1.94%
ARIMA (1,1,1)	1.99%
ARIMA (0,1,2)	1.95%

Table 3 shows the ARIMA (0,1,1) model is the most effective, as it achieves the lowest AIC value of 3227.538 and the smallest MAPE value of 1.94%.

Diagnostic checking was conducted to verify whether the ARIMA (0,1,1) model satisfies the classical ARIMA assumptions. The diagnostic plots of the residuals are presented in Figure 5, which include the normal probability plot, histogram, residuals versus fitted values, and residuals versus order.

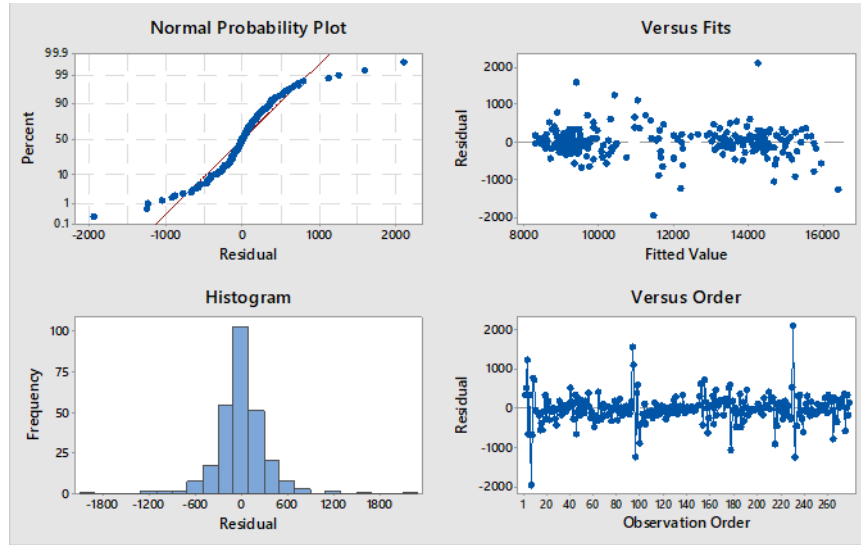


Figure 5. Residuals Plots for USD

As shown in Figure 5, the residuals are approximately normally distributed, indicated by the nearly linear pattern in the normal probability plot and the bell-shaped histogram centered around zero. The residuals are randomly scattered around the zero line in both the residual versus fitted and residual versus order plots, suggesting homoskedasticity and the absence of autocorrelation. Furthermore, the Ljung–Box test results support these findings, with p-values greater than 0.05 at several lags ($p = 0.430, 0.596, 0.814, \text{ and } 0.857$), indicating that the residuals are independent. Therefore, it can be concluded that the ARIMA (0,1,1) model satisfies the normality, independence, and constant variance assumptions. The diagnostic results confirm that the ARIMA (0,1,1) model is statistically adequate and suitable for forecasting the USD and IDR exchange rate. Based on the diagnostic results and the performance evaluation, the ARIMA (0,1,1) model is deemed reliable for forecasting the USD and IDR exchange rate, as it fulfills all statistical assumptions and yields the lowest AIC and MAPE values.

This research employs various combinations of hyperparameter settings to construct the GRU model. Key hyperparameters influencing the performance and learning of the GRU model include the number of neurons, learning rate, and epochs. Table 4 shows the hyperparameter combinations utilized in this research.

Table 4. Hyperparameter GRU

Hyperparameter	Value
Dropout	0.2
Validation Split	0.2
Number of Neurons	[20, 32, 64, 100, 200]
Learning Rate	[0.01, 0.001, 0.0001]

The GRU model was built and trained following these steps: data normalization, model construction, training with an 80:20 data split, and hyperparameter tuning as listed in Table 4. Model performance was evaluated using MAPE, and the best configuration was selected based on the smallest MAPE value. In the GRU model, a Dropout rate of 0.2 is used, which randomly omits some neurons during training. This helps the GRU model become more robust and better at generalizing to new data. Additionally, a validation split of 0.2 is used, indicating that 20% of the training data is set aside for validation during the GRU model training process. This combination of hyperparameter settings is applied to exchange rate

training data, and forecast accuracy is tested using test data. Furthermore, from the combination of hyperparameter settings that have been applied, the value of each MAPE can be seen in Table 5.

Table 5. MAPE Value of GRU Method for Exchange Rate

Number of Neurons	Epoch	Learning Rate	MAPE
200	200	0.01	1.74%
100	500	0.01	2.00%
200	500	0.01	1.78%
100	200	0.01	2.45%
100	100	0.01	2.52%
64	200	0.01	1.89%
200	100	0.01	2.14%
64	500	0.01	1.94%
64	100	0.01	1.75%
200	100	0.001	23.95%
200	200	0.001	23.43%
200	500	0.001	24.34%
20	500	0.01	2.77%
32	500	0.01	2.47%
100	200	0.001	24.9%

From Table 5, it can be seen that the best model with the number of neurons of 200, epoch 200, and learning rate 0.01 produces the smallest MAPE value of 1.74%. The best GRU configuration used 200 neurons, 200 epochs, and a learning rate of 0.01. The model was then tested on out sample data to evaluate its predictive performance. The results are shown in Table 6.

Tabel 6. Actual and Predicted Exchange Rate (GRU Model)

Period	Actual	Predicted (GRU)
January 2023	14,979	14,720
February 2023	15,274	15,060
March 2023	15,062	15,310
April 2023	14,751	14,990
May 2023	14,969	15,180

Table 6 shows that the predicted values generated by the GRU model closely follow the actual data trend, confirming the model's reliability in forecasting the Rupiah and USD exchange rate.

The Mean Absolute Percentage Error values for ARIMA (0,1,1) and GRU can be seen in Table 7.

Tabel 7. MAPE Values for ARIMA (0,1,1) and GRU

Model	MAPE
ARIMA (0,1,1)	1.94%
GRU	1.74%

Based on Table 7, it can be concluded that both ARIMA and GRU have small MAPE values, indicating excellent model performance. The GRU model has the best MAPE value. This is in accordance with previous research by Ridwan et al., 2023 which also states that the GRU model is better than ARIMA.

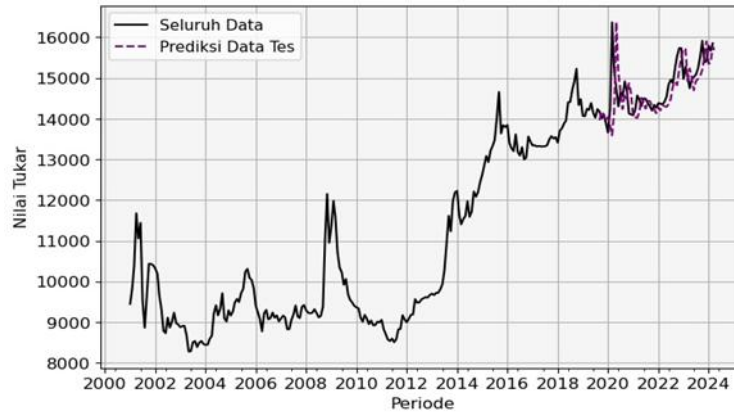


Figure 6. Prediction Results of GRU model for Training Data and Test Data

Based on the prediction plots in Figures 6, the GRU model is able to predict the USD to rupiah exchange rate more accurately than ARIMA. The predictions of the GRU model follow the trend of the test data very well, indicating that this model can be used to predict the future USD to rupiah exchange rate with high accuracy compared to the ARIMA model. The GRU model, as a more complex machine learning model, is able to learn more complicated patterns and relationships in the data, resulting in more accurate predictions. Furthermore, forecasting is carried out for the month of April 2024, the forecasting results can be seen in Table 8.

Tabel 8. Forecast for April 2024

Model	Forecast
Current Data	Rp. 16,249.00
ARIMA (0,1,1)	Rp. 15,857.68
GRU	Rp. 16,399.91

Based on Table 8, it can be concluded that the predicted value of GRU is closer to the actual data than the predicted value of ARIMA. Prediction results from ARIMA tend to approach previous data, while GRU predictions tend to follow the actual exchange rate movement in April. These results are consistent with previous research by Ridwan et al. (2023), which also found that GRU outperformed ARIMA in forecasting financial time series data. However, unlike previous studies that focused on stock prices, this study specifically applies both models to the Rupiah–USD exchange rate, providing new empirical evidence of GRU’s superior predictive ability in exchange rate forecasting. To further evaluate the model’s short-term forecasting performance, predictions were extended for the period from April 1 to April 10, 2024, as shown in Table 9.

Tabel 9. Forecast for April 2024

Date	Actual	GRU Forecast (Rp)
1 April 2024	15,952.36	15,960.84
2 April 2024	15,988.55	15,995.73
3 April 2024	16,013.67	16,025.46
4 April 2024	16,002.61	16,041.92
5 April 2024	15,986.53	16,058.43
6 April 2024	–	16,071.28
7 April 2024	–	16,083.55
8 April 2024	–	16,094.23
9 April 2024	–	16,106.72
10 April 2024	–	16,118.34

Based on Table 9, The GRU forecasting model was applied to predict the short-term movement of the Rupiah exchange rate for the period from April 1 to April 10, 2024. The predicted values show a gradual upward trend, indicating a slight depreciation of the Rupiah against the USD. This trend is consistent with the actual data observed from Bank Indonesia in early April 2024. For certain dates, actual data were unavailable because Bank Indonesia does not publish exchange rates on weekends or public holidays; therefore, only the predicted values are presented for those dates.

The results of this study are consistent with the findings Gustiansyah et al., (2023) and Ridwan et al., (2023), who demonstrated that the GRU model provides superior forecasting accuracy compared to ARIMA due to its ability to capture nonlinear and volatile patterns in financial time series data. On the other hand, ARIMA remains effective for modeling shortterm fluctuations and moderate volatility because of its simple linear structure and stable performance with limited datasets (Meher et al., 2021). However, prior studies have seldom examined both models within the context of Indonesia's currency, particularly the Rupiah and USD exchange rate, resulting in a lack of understanding of their comparative robustness under Indonesia's market volatility. This study seeks to fill that gap by providing empirical evidence that the GRU model yields more accurate and adaptive forecasts than ARIMA when dealing with nonlinear and highly volatile movements of the Rupiah.

5. CONCLUSION

Based on the results of the analysis, it can be concluded that the GRU model performs better than the ARIMA model in predicting the USD selling rate against the Rupiah. The GRU model achieved a lower MAPE value of 1.74% compared to ARIMA's 1.94%, indicating higher prediction accuracy. GRU can effectively capture nonlinear and adaptive patterns, while ARIMA is limited to simpler linear relationships. These findings answer the research objectives by demonstrating that deep learning methods, such as GRU, can outperform traditional time series models in exchange rate forecasting. This research provides practical implications for financial analysts and policymakers, particularly in improving short-term currency prediction and decision-making related to exchange rate fluctuations. Future research could explore hybrid models that combine GRU with optimization techniques or test the model's performance using higher frequency (daily or hourly) data to further enhance forecasting accuracy.

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