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Application of Recurrent Neural Network Bi-Long Short-Term Memory, Gated Recurrent Unit and Bi-Gated Recurrent Unit for Forecasting Rupiah Against Dollar (USD) Exchange Rate

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Abstract

Foreign exchange rates have a crucial role in a country's economic development, influencing long-term investment decisions. This research aims to forecast the exchange rate of Rupiah to the United States Dollar (USD) by using deep learning models of Recurrent Neural Network (RNN) architecture, especially Bi-Long Short-Term Memory (Bi-LSTM), Gated Recurrent Unit (GRU), and Bi-Gated Recurrent Unit (Bi-GRU). Historical daily exchange rate data from January 1, 2013 to November 3, 2023, obtained from Yahoo Finance, was used as the dataset. The model training and evaluation process was performed based on various parameters such as optimizer, batch size, and time step. The best model was identified by minimizing the Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Among the models tested, the GRU model with Nadam optimizer, batch size 16, and timestep 30 showed the best performance, with MSE 3741.6999, RMSE 61.1694, MAE 45.6246, and MAPE 0.3054%. The forecast results indicate a strengthening trend of the Rupiah exchange rate against the USD in the next 30 days, which has the potential to be taken into consideration in making investment decisions and shows promising economic growth prospects for Indonesia.

Keyword: Bi-LSTM, Bi-GRU, Foreign Exchange Rate, Gated Recurrent Unit, Prediction

1. INTRODUCTION

The financial value of a country can be assessed by comparing its currency to that of another. Currencies fluctuate between countries due to changes in the supply and demand for specific currencies [1]. Uncertainty in economic development in Indonesia is influenced by fluctuations in foreign exchange rates [2]. These factors significantly influence the prices of imported goods [3] and stock prices [4]. The stock market stands as a pivotal sector profoundly impacting a nation's economy [5] Currency exchange rate fluctuations wield considerable influence over investors, particularly in long-term investments [6]. These fluctuations, driven by diverse and nonlinear factors, pose challenges for investors in accurately forecasting optimal prices [7]. Employing a Deep Learning methodology enables the prediction of fluctuations in the Rupiah-to-Dollar (USD) exchange rate [8].

Deep learning allows for the characterization of individual influential factors [9]. Among the algorithms of deep learning, the Recurrent Neural Network (RNN) stands out—an architecture that processes data sequentially as distinct segments entering the network. Each segment's data amalgamates with the preceding segment's output data, serving as subsequent input [10]. RNN exhibits proficiency in tackling time-series problems due to its inherent capability to theoretically retain information across various time steps [9], [11] . There are several types of RNN architecture, such as Bi-Long Short-Term Memory (Bi-LSTM), Gated Recurrent Unit (GRU), and Bi-Gated Recurrent Unit (Bi-GRU). These three RNN architectures offers good performance for time-series data, Hansun et al. conducted research in 2022 [12] that focused on implementing Long Short-Term Memory (LSTM) and Bi-LSTM for forex forecasting with five major currencies of USD exchange rate finds LSTM has less training time than Bi-LSTM. However, Bi-LSTM has greater predictive performance than LSTM models. Another study conducted by Saud and Sakya (2020) [13], comparing prediction performance of some RNN architecture variants such as Vanilla Recurrent Neural Network (VRNN), LSTM and GRU for predicting stock prices. This research shows LSTM and GRU outperforms VRNN in predicting stock prices. It also found GRU became the best model for predicting stock prices. Lastly, Karim and Ahmed conducted a study in 2021 [14] showing Bi-GRU has better stability and fewer parameters, this can be identified through assessment metrics such as smaller Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE) and higher R2 compared to Bi-LSTM.

Bidirectional LSTM (Bi-LSTM) extends the LSTM architecture by employing two LSTM layers on the input data. The initial LSTM processes the input sequence (forward layer), while a second LSTM processes the inverted form of the data (backward layer). This approach enhances both learning capabilities and accuracy but demands an extensive training period [15]. GRU a simplified variant of the LSTM network, comprises only two gate layers: the reset gate and the update gate. The reset gate determines the extent of previous memory information to discard [16]. Bidirectional-GRU (Bi-GRU) represents an advancement by merging the reverse RNN and GRU. Structurally akin to Bi-LSTM, Bi-GRU diverges in its cyclic units, allowing both adversarial networks to concurrently leverage forward and backward information. Bi-GRU exhibits simplicity compared to Bi-LSTM, mirroring the simpler nature of GRU in contrast to LSTM [17].

Pontoh et al. conducted a study in 2021 that focused on predicting the Rupiah exchange rate utilizing LSTM models [18]. Their findings revealed the LSTM model's proficiency in predicting the Rupiah exchange rate, exhibiting an error margin of 4.765% in day 5 predictions. In a separate study in 2022, Hansun et al. identified the superior predictive performance of Bi-LSTM over LSTM models for forecasting forex market movements [12]. Additionally, Islam and Hossain's research in 2021 compared GRU-LSTM hybrid models against LSTM and GRU individually, concluding that GRU outperformed LSTM, while the GRU-LSTM hybrid model surpassed GRU's performance [19]. Karim and Ahmed's 2021 research determined Bi-GRU as a superior predictor of stock prices compared to Bi-LSTM models [14].

These discussions collectively serve as the foundation for the author's current research, which centers on the application of Bi-LSTM, GRU, and Bi-GRU models in forecasting the Rupiah-to-Dollar (USD) exchange rate.

2. MATERIAL AND METHOD

The research starts with collecting data, utilizing historical daily Rupiah-to-Dollar (USD) exchange rates spanning the last 10 years from January 1, 2013, to November 3, 2023, comprising 2825 records retrieved from Yahoo Finance. The data is processed by normalizing it within the range of 0 to 1 and employing the sliding window (time step) method to facilitate predictions. The study incorporates Bi-Long Short-Term Memory, Gated Recurrent Unit, and Bi-Gated Recurrent Unit methods, experimenting with time steps of 5, 10, and 30 [20], [21]. The data is split into training and testing sets using an 80:20 Holdout technique, assigning 80% for training and 20% for testing. Various batch sizes of 8, 16, and 32, along with optimization techniques such as Adam, AdamW, and Nadam, are employed to enhance the model's performance. Assessment of the trained RNN models is conducted using metrics including MSE, RMSE, MAE, and MAPE to determine the most effective model. The research stages are depicted in Figure 1.

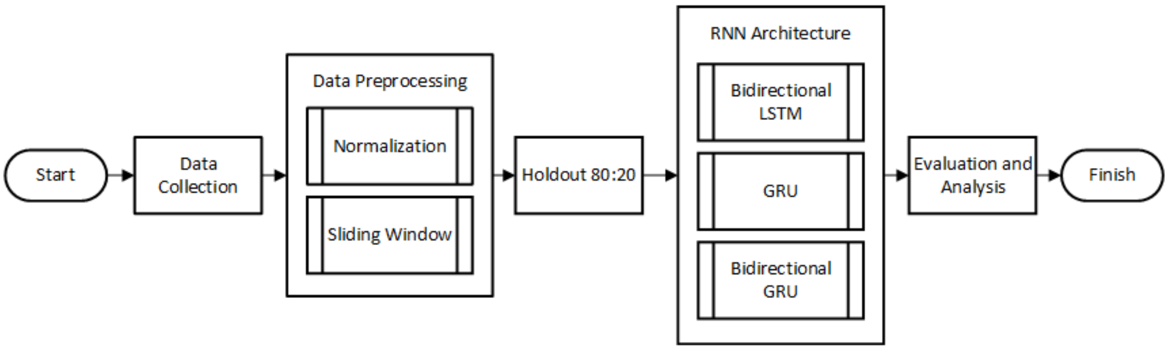

Figure 1. Research Methodology

2.1. Data Collecting

The data collection process involves utilizing the Yahoo Finance API alongside the Python programming language and the yfinance library. This study leverages historical data regarding the daily Rupiah-to-Dollar (USD) exchange rate, specifically identified by the data code IDR=X. The dataset was retrieved from Yahoo Finance website (https://finance.yahoo.com/quote/IDR%3DX/history). This study using historical data from last 10 years from January 1, 2013, to November 3, 2023, comprising 2825 records retrieved from Yahoo Finance. It encompasses seven attributes: Date, Open, High, Low, Close, Adj Close, and Volume. Notably, this research focuses solely on a univariate approach, utilizing only one variable from dataset, the Close attributes as close prices to predict the Rupiah to Dollar (USD) exchange rate [22], [23], [24], [25].

2.2. Foreign Exchange

Foreign Exchange is one of the largest financial markets in the world [9], [12], [19]. Forex is a core component of every country's financial market, and exchange rate stability is essential for macroeconomic stability [7] Currency rates are influenced by several factors, such as the country's economy, politics, society, international situation [9], [23]. Currency rate prediction can help investors make wise decisions to increase profits and reduce risks [9], [22].

2.3. Bidirectional Long Short-Term Memory (Bi-LSTM)

Bi-LSTM is a variation of LSTM that allows additional training by traversing the input data twice and can capture information in both forward and backward directions [26]. The Bi-LSTM computation process is defined by the following equation [27].

$$\overrightarrow{\mathrm{forward}_t} = f\left(U_f X_t + W_f \overrightarrow{h_{t-1}} + \vec{b}\right) \tag{1}$$

$$\overleftarrow{\mathrm{backward}_t} = f\left(U_b X_t + W_b \overleftarrow{h_{t+1}} + \overleftarrow{b}\right) \tag{2}$$

$$\mathrm{output}_t = g\left(J\left[\overrightarrow{\mathrm{forward}_t V_f} + \vec{d}; \overleftarrow{\mathrm{backward}_t V_b} + \overleftarrow{d}\right] + c\right) \tag{3}$$

Explanation:

$\overrightarrow{\mathrm{forward}_t}$	: Result of forward layer
$\overleftarrow{\mathrm{backward}_t}$	: Result of backward layer
output_t	: The probability value generated by combining $\overrightarrow{\mathrm{forward}_t}$ and $\overleftarrow{\mathrm{backward}_t}$
f, g	: Nonlinear activation function
h	: Value of the hidden layer
U, W, V	: Weight matrices
b, d, c	: Bias value

2.4. Gated Recurrent Unit (GRU)

GRU is a simple variant of LSTM that has two gates, which are "update gate" consisting of input, forget gates, and "reset gate". GRU does not have additional memory cells to store information, therefore it can only control information within the unit [28]. The formulation of GRU is formulated as follows [29].

$$Z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \tag{4}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \tag{5}$$

$$\tilde{h}_t = \tanh(W_h \cdot [r_{t-1}, x_t] + b_c) \tag{6}$$

$$h_t = (1 - Z_t) \times h_{t-1} + Z_t \times \tilde{h}_t \tag{7}$$

Explanation:

Z_t	: Update gate
r_t	: Reset gate
$\tilde{h}_t$	: Candidate hidden state
h_t	: Final hidden state
h_{t-1}	: Previous state
σ	: Sigmoid gate network layer
tanh	: Hyperbolic tangent activation function layer
W_h, W_z, W_r	: Weight matrices

2.5. Bidirectional Gated Recurrent Unit (Bi-GRU)

Unlike GRU, which can only predict the output for the next moment based on temporal sequence information from the previous moment, Bi-GRU combines information from the input sequence in both forward and backward directions [30]. The formulation in Bi-GRU computation involves performing GRU calculations in two directions. The formula for Bi-GRU calculation is as follows.

$$\overrightarrow{h_t} = \tanh\left(\overrightarrow{W_h} \cdot \left[\overrightarrow{h_{t-1}}, x_t\right] + \overrightarrow{b_h}\right) \tag{8}$$

$$\overleftarrow{h_t} = \tanh\left(\overleftarrow{W_h} \cdot \left[\overleftarrow{h_{t-1}}, x_t\right] + \overleftarrow{b_h}\right) \tag{9}$$

$$h_t = \overrightarrow{h_t} \oplus \overleftarrow{h_t} \tag{10}$$

2.6. Sliding Window Method (Time Steps)

The sliding window technique involves partitioning a time series data sequence into two segments: the initial segment serves as the input window values, while the subsequent segment represents the predicted values [31]. This iterative process advances step by step, shifting one step at a time through the dataset, acquiring multiple samples from the training set. This method effectively captures temporal patterns within time series data, encompassing information from historical to the most recent data points [32].

2.7. Optimizer

Different optimizers possess distinct traits. Commonly employed optimizers for analysing time series data include Adam, Adam with Weight Decay (AdamW), and Nesterov Adam (Nadam) [7], [33]. Optimizer Adam optimizer stands out as a highly efficient and adaptive [34]. AdamW represents a modified optimizer incorporating weight decay, imparting a gradient regularization effect [35], [36] Lastly, Nadam emerges as an advancement of the Adam optimizer, enhancing weight optimization by integrating Nesterov momentum [37].

2.8. Evaluation Metrics

The performance estimation of the RNN model is done with several evaluation metrics such as evaluation and analysis of Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) which can be formulated with the following equations [14], [23].

$$MSE = \frac{1}{k}\sum_{j=1}^{k} \left(y_j - \bar{y}_j\right)^2 \tag{11}$$

$$RMSE = \sqrt{\frac{1}{k}\sum_{j=1}^{k} \left(y_j - \bar{y}_j\right)^2} \tag{12}$$

$$MAE = \frac{1}{k}\sum_{j=1}^{k} \left|y_j - \bar{y}_j\right| \tag{13}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{14}$$

3. RESULTS AND DISCUSSION

The forecasting of the Rupiah's exchange rate to the USD Dollar involved employing Bi-LSTM, GRU, and Bi-GRU algorithms through multiple experiments aimed at obtaining the most effective model. These experiments encompassed various time steps (5, 10, and 30), different optimizers such as Adam, AdamW, and Nadam, and varied batch sizes (8, 16, and 32). To refine the models, a learning rate scheduler was implemented, starting at 0.001 and reducing to 0.00001 after 30 epochs, totalling 350 epochs during the training phase.

The model evaluation process employs several metrics such as MSE, RMSE, MAE, and MAPE. These four metrics are commonly utilized to assess the performance of regression models [9], [38]. MSE is a metric that measures the accuracy of estimations by computing the average squared difference between projected and actual values [23]. Similarly, RMSE calculates the square root of the average squared deviation to determine the difference between expected and actual values [39]. In contrast, MAE evaluates the average magnitude of mistakes between predicted values and their actual equivalents [14]. MAPE measures the average of mean absolute percent errors [40]. A lower MSE, RMSE, MAE, MAPE suggests better estimating accuracy [14], [38]. Following Bi-LSTM modeling, the Nadam optimizer, along with a batch size of 8 and 10 timesteps, emerged as the best-performing model, showcasing MSE of 3915.4732, RMSE of 62.5737, MAE of 46.7269, and MAPE of 0.3127%. Bi-LSTM using Nadam optimizer with it is own parameter has the lowest MSE, RMSE, MAE, MAPE accross Bi-LSTM models indicates this model performs well for forecasting of the Rupiah's exchange rate to the USD Dollar. Comprehensive details of Bi-LSTM models, refer to the results presented in Table 1. depicting the outcomes of all Bi-LSTM models.

Table 1. Evaluation Results of Bi-LSTM Algorithm Modeling

Experiment			Bi-LSTM			
Optimizer	Batch size	Timestep	MSE	RMSE	MAE	MAPE
Adam	8	5	4430.7813	66.5641	50.7697	0.3384
Adam	8	10	4138.8094	64.3335	48.8730	0.3267
Adam	8	30	3931.2972	62.7000	47.0971	0.3150
Adam	16	5	5024.6755	70.8849	54.1665	0.3623
Adam	16	10	4741.1627	68.8561	52.7091	0.3517
Adam	16	30	4469.2031	66.8520	50.4886	0.3376
Adam	32	5	5542.4723	74.4477	56.7920	0.3798
Adam	32	10	5277.0146	72.6430	55.5966	0.3712
Adam	32	30	5136.5697	71.6698	53.8691	0.3601
AdamW	8	5	4621.7583	67.9835	51.9293	0.3458
AdamW	8	10	3978.6648	63.0766	47.6352	0.3189
AdamW	8	30	4284.6756	65.4574	48.2886	0.3237
AdamW	16	5	5066.6960	71.1807	54.3371	0.3634
AdamW	16	10	4676.0743	68.3818	52.3198	0.3491
AdamW	16	30	4273.0646	65.3686	48.8776	0.3271
AdamW	32	5	5595.9764	74.8062	56.8741	0.3804
AdamW	32	10	4952.7110	70.3755	52.3838	0.3503
AdamW	32	30	5215.9224	72.2213	54.5693	0.3647
Nadam	8	5	4474.6093	66.8925	50.9849	0.3397
Nadam	8	10	3915.4732	62.5737	46.7269	0.3127
Nadam	8	30	4327.7440	65.7855	49.4773	0.3303
Nadam	16	5	5143.9641	71.7214	55.1725	0.3688
Nadam	16	10	4574.4540	67.6347	51.5265	0.3440
Nadam	16	30	4535.8050	67.3483	50.4030	0.3372
Nadam	32	5	5589.6352	74.7638	57.2957	0.3831
Nadam	32	10	5033.2644	70.9455	53.4433	0.3573
Nadam	32	30	5128.9404	71.6166	54.0068	0.3610

The most effective GRU model was identified using the Nadam optimizer, batch size 16, and 30 timesteps, achieving an MSE value of 3741.6999, RMSE of 61.1694, MAE of 45.6246, and MAPE of 0.3054%. GRU modelling using Nadam Optimizer resulted in the lowest values for each performance metric, indicating that GRU is superior at forecasting the Rupiah exchange rate to the USD Dollar. Detailed overview of all GRU modeling results is available in Table 2.

Table 2. Evaluation Results of GRU Algorithm Modeling

Experiment			GRU			
Optimizer	Batch size	Timestep	MSE	RMSE	MAE	MAPE
Adam	8	5	3779.1159	61.4745	46.0093	0.3080
Adam	8	10	3885.2514	62.3317	47.2738	0.3159
Adam	8	30	4363.6444	66.0578	50.1230	0.3349
Adam	16	5	4345.4717	65.9201	49.8486	0.3336
Adam	16	10	3882.3160	62.3082	46.4493	0.3109
Adam	16	30	3766.8007	61.3742	45.7831	0.3064
Adam	32	5	4659.9514	68.2638	51.8507	0.3466
Adam	32	10	4298.6091	65.5637	49.1672	0.3289
Adam	32	30	4195.9679	64.7762	48.5991	0.3254
AdamW	8	5	3860.1778	62.1303	46.2072	0.3094
AdamW	8	10	3852.6974	62.0701	46.9520	0.3138
AdamW	8	30	3846.3824	62.0192	46.8660	0.3135
AdamW	16	5	4220.7012	64.9669	48.6837	0.3259
AdamW	16	10	3951.7281	62.8627	47.1601	0.3156
AdamW	16	30	3750.2839	61.2395	45.7587	0.3062
AdamW	32	5	4604.9008	67.8594	50.9906	0.3411
AdamW	32	10	4523.2905	67.2554	50.9045	0.3400
AdamW	32	30	4179.2959	64.6474	48.5810	0.3250
Nadam	8	5	3944.4518	62.8048	46.7980	0.3134
Nadam	8	10	3918.3721	62.5969	47.2323	0.3158
Nadam	8	30	3766.6199	61.3727	46.1527	0.3088
Nadam	16	5	4217.3605	64.9412	47.9481	0.3212
Nadam	16	10	3976.1317	63.0565	47.5138	0.3178
Nadam	16	30	3741.6999	61.1694	45.6246	0.3054
Nadam	32	5	4603.0532	67.8458	51.4150	0.3439

Experiment			GRU			
Optimizer	Batch size	Timestep	MSE	RMSE	MAE	MAPE
Nadam	32	10	4338.8661	65.8700	49.5562	0.3317
Nadam	32	30	3970.3347	63.0105	47.3913	0.3171

From the Bi-GRU modeling analysis, the most effective model was achieved by employing the Nadam optimizer, utilizing a batch size of 16 and 30 timesteps. This model showcased notable metrics MSE of 3814.2325, RMSE of 61.7594, MAE of 46.1240, and MAPE of 0.3087%. Bi-GRU modelling offers inferior predictive performance than the GRU algorithm, but outperforms Bi-LSTM in forecasting. Both GRU and Bi-GRU models train faster due to their fewer parameters [13], with GRU achieving the quickest training time. However, Bi-LSTM requires more training time. Comprehensive details of all Bi-GRU modeling results are documented in Table 3.

Table 3. Evaluation Results of Bi-GRU Algorithm Modeling

Experiment			Bi-GRU			
Optimizer	Batch size	Timestep	MSE	RMSE	MAE	MAPE
Adam	8	5	3966.3704	62.9791	47.8716	0.3202
Adam	8	10	4042.2024	63.5783	47.5792	0.3185
Adam	8	30	3993.8556	63.1969	47.7552	0.3190
Adam	16	5	4822.0791	69.4411	52.8656	0.3537
Adam	16	10	4383.6936	66.2094	49.4380	0.3309
Adam	16	30	3885.2224	62.3315	46.7495	0.3128
Adam	32	5	5253.6142	72.4818	55.3120	0.3700
Adam	32	10	5102.5243	71.4319	54.0826	0.3615
Adam	32	30	4626.7878	68.0204	51.6684	0.3454
AdamW	8	5	4140.8939	64.34977	48.8054	0.3259
AdamW	8	10	4070.9422	63.8039	47.4904	0.3180
AdamW	8	30	3837.0555	61.9439	46.4631	0.3109
AdamW	16	5	4925.9867	70.1853	53.6394	0.3588
AdamW	16	10	4473.1840	66.8818	50.4026	0.3373
AdamW	16	30	3929.3509	62.6845	47.0323	0.3147
AdamW	32	5	5223.4857	72.2736	55.1332	0.3688
AdamW	32	10	5239.1382	72.3818	55.1205	0.3683
AdamW	32	30	4558.1630	67.5141	50.5764	0.3385
Nadam	8	5	3991.8672	63.1812	47.7555	0.3189
Nadam	8	10	3856.8540	62.1035	47.7814	0.3197
Nadam	8	30	3820,6449	61,8113	46,6405	0,3119
Nadam	16	5	4856.3487	69.6875	53.5669	0.3581
Nadam	16	10	4263.7292	65.2972	49.2281	0.3292
Nadam	16	30	3814.2325	61.7594	46.1240	0.3087
Nadam	32	5	5219.7303	72.2477	55.2093	0.3693
Nadam	32	10	4959.9873	70.4271	52.9562	0.3543
Nadam	32	30	4402.8839	66.3542	49.7838	0.3332

3.1. Evaluation and Analysis

Based on the results of the evaluation and analysis that has been done, the best model is obtained, which is the GRU Algorithm with the Nadam optimizer, batch size 16 and timesteps 30 with an MSE value of 3741.6999, RMSE of 61.1694, MAE of 45.6246, and MAPE of 0.3054%. MAPE value within the range of 0-0.5 is considered as excellent, while MAE and RMSE value within 10-100 is not categorized as low [9]. Visualization of the best model graph can be seen in Figure 5. and the prediction of the Rupiah to Dollar (USD) exchange rate on the testing dataset can be seen in Figure 6.

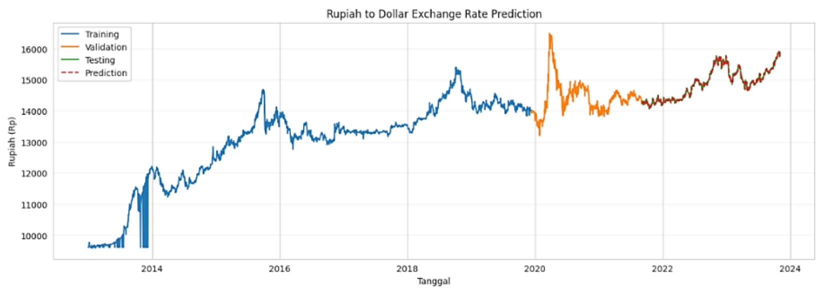

Figure 5. Visualization of the Best Model of GRU Algorithm

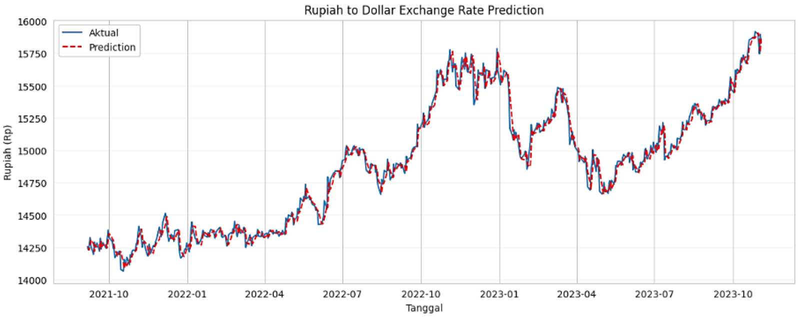

Figure 6. Prediction of Rupiah to Dollar Exchange Rate (USD) using GRU Algorithm

The GRU algorithm demonstrates superior performance compared to the Bi-LSTM and Bi-GRU algorithms when forecasting the Rupiah-to-Dollar (USD) exchange rate. Experimental findings indicate that the Nadam optimizer outperforms Adam and AdamW. Notably, optimal parameters involving the Nadam optimizer, a batch size of 16, and 30 timesteps yield the most accurate modeling for predicting the Rupiah-to-Dollar (USD) exchange rate. Furthermore, the experimental results suggest that higher sliding window values contribute to more precise modeling among the three algorithms used.

3.2. Exchange Rate Forecast and Investment Implications

The forecasted Rupiah to Dollar (USD) exchange rate for the next 30 days suggests an increase in the Rupiah's value in December 2023. This indicates a strengthening trend for the Rupiah against the Dollar in the upcoming month, potentially influencing investor considerations regarding investments in the Indonesian economy. Salisu and Vo (2021) [41] suggest that countries with promising prospects in the foreign exchange market are more likely to attract investors seeking to optimize investment returns in their stock exchanges. Conversely, nations with poorly performing currencies in the foreign exchange market may attract less investor interest. According to Gunawan and Bawono's research, currency exchange rates can affect the company's production costs and dividends received by investors [42]. Thus investment decisions by investors are strongly influenced by market conditions of foreign currencies[43].

These study findings highlight Indonesia's promising economic growth potential. It is supported by two main potential factors, which are market size and economic growth. According to Fernandez et al. (2020) [44], Indonesia's economy has experienced robust growth over the past two decades, with annual average growth rates exceeding 5%, nearly double the global average. The World Bank's national accounts data from 2019 indicates that growth averaged 5.24% during the 2000s and further increased to 5.36% in the period spanning 2011 to 2018. the findings in this study are also supported by previous research by Rosyadi et al (2022) that the exchange rate wields a significant impact on the economic growth of Indonesia [45]. Figure 7. presents the forecasted Rupiah to Dollar (USD) exchange rate for the next month.

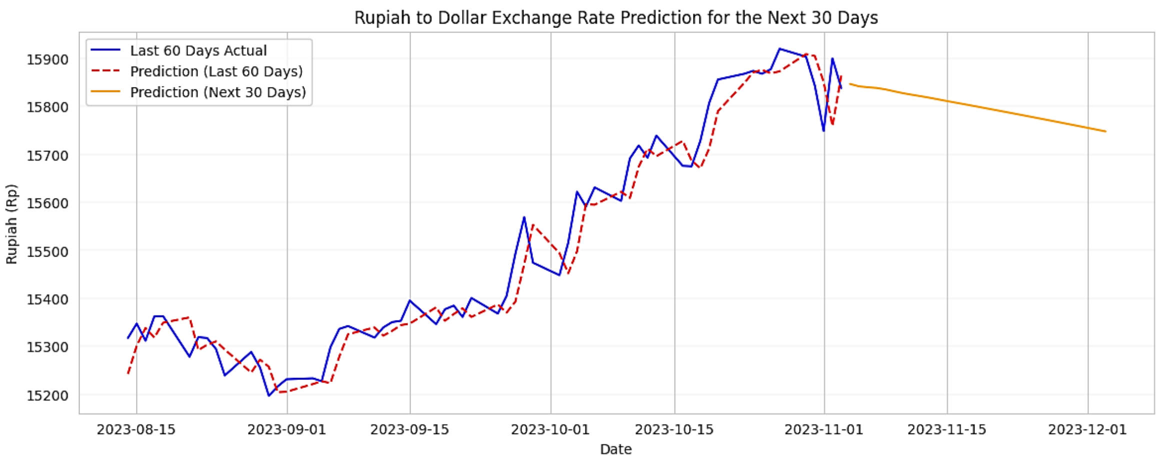

Figure 7. Forecasted Rupiah to Dollar (USD) Exchange Rate for December 2023

4. CONCLUSION

Based on the results and analysis conducted, it can be concluded that The Bi-LSTM, GRU, and Bi-GRU algorithms effectively forecast the Rupiah to Dollar (USD) exchange rate. Notably, the GRU model with the Nadam optimizer, utilizing a batch size of 16 and 30 timesteps, emerges as the top-performing model, showcasing an MSE of 3741.6999, RMSE of 61.1694, MAE of 45.6246, and MAPE of 0.3054%. Because this model had resulted in the lowest values for each performance metric, indicating that GRU is very good at forecasting the Rupiah exchange rate to the USD Dollar. Besides, MAPE value within the range of 0-0.5 is considered as excellent, while MAE and RMSE value within 10-100 is not categorized as low. The utilization of the Nadam optimizer demonstrates superiority over Adam and AdamW, significantly enhancing the predictive capability of the Bi-LSTM, GRU, and Bi-GRU models. Leveraging this superior GRU model, the forecast indicates an anticipated strengthening trend of the Rupiah against the Dollar for the upcoming month. This forecast insight might influence potential investors exploring opportunities within Indonesia's growing economy.

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