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IMPROVING EXCHANGE RATE PREDICTION ACCURACY WITH 1D-CNN-BiGRU AND WALK FORWARD ANALYSIS

HAANA LAHANDA PUTRI SAMSI, GUMGUM DARMAWAN*, YUYUN HIDAYAT
Department of Statistics, Universitas Padjadjaran, Bandung, Indonesia

Abstract: This study was conducted to improve the accuracy of forecasting the exchange rate of the Rupiah against the Japanese Yen, which was crucial for economic actors in managing risks, enhancing investment efficiency, and supporting adaptive financial policies. The research aimed to develop a forecasting method with the lowest possible error rate (MAPE) to address the limitations of conventional models and provide more accurate insights for decision- makers. The method used was a hybrid approach combining a 1D-Convolutional Neural Network (1D-CNN) and a Bidirectional Gated Recurrent Unit (BiGRU), along with a walk-forward analysis strategy to capture trend patterns and short-term volatility in exchange rates. The results showed that the Hybrid 1D-CNN-BiGRU model effectively predicted exchange rate fluctuations for the next five days, achieving a MAPE value below 1%, indicating higher accuracy compared to previous approaches. The conclusion of this study was that the Hybrid 1D-CNN-BiGRU model was an effective forecasting method for the Rupiah-to-Yen exchange rate, providing a stronger foundation for economic actors in making currency transaction decisions. The main contribution of this research was the implementation of a combined method that had not been previously applied in exchange rate forecasting, opening new opportunities for further research in exploring other hybrid models to improve prediction accuracy in various economic and financial fields.

Keywords: exchange rate forecasting; hybrid 1D-CNN-BiGRU; walk forward analysis; Japanese Yen; currency volatility.

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*Corresponding authors
E-mail addresses: gumgum@unpad.ac.id
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1. INTRODUCTION

The exchange rate of the Rupiah against the Japanese Yen shows a long-term declining trend, reflecting economic stability in the post-pandemic period. A more stable economic condition after the pandemic plays a significant role in the movement of the exchange rate between these two currencies [1], [2], [3]. Additionally, both global and domestic factors contribute to exchange rate fluctuations [4], [5], [6], making it increasingly important for various stakeholders to understand these trends [7], [8].

As a stable currency widely used in Indonesia's economic transactions, the Japanese Yen holds a significant role in bond issuance and government investments. The stability of the Yen makes it a preferred choice in trade and international transactions [9], [10]. Moreover, many Indonesian companies have debts denominated in Yen [11], making the exchange rate fluctuations between the Rupiah and Yen directly impact investment costs and profitability in Indonesia [12].

Short-term exchange rate fluctuations create both opportunities and risks for economic players. Therefore, hedging strategies become crucial in minimizing the impact of exchange rate volatility [8], [13], [14]. Investors can take advantage of these fluctuations to maximize profits through more optimized investment strategies [15], [16], [17]. By understanding exchange rate movement patterns, economic decision-making can be carried out more effectively, highlighting the need for accurate forecasting methods [6], [17], [18].

To improve the accuracy of Rupiah-to-Yen exchange rate forecasting, various statistical and machine learning methods have been developed. These approaches offer advantages over conventional methods, particularly in capturing complex patterns in exchange rate data [19], [20], [21]. The combination of statistical techniques and artificial intelligence enables better prediction accuracy, making the selection of an appropriate forecasting method a crucial factor in this study [7], [22].

Previous research has employed linear regression models to predict exchange rates, but these models could only explain 43.1% of the total data variance. This limitation indicates that conventional models are less effective in capturing complex patterns and sudden fluctuations [20], [21], [23]. Additionally, models such as ARIMA and ARIMA-GARCH, which are frequently used for exchange rate forecasting, have not been able to optimally address volatility, resulting in less accurate predictions [22], [23], [24]. This inaccuracy affects economic decision-making, necessitating a more innovative approach.

The ARIMA-GARCH model used in previous studies produced a relatively high forecasting error, with a MAPE value of 19.29% [25]. This substantial error highlights the need for more accurate methods that can capture long-term trends and significant exchange rate fluctuations. The limitations of conventional models in detecting dynamic patterns further emphasize the importance of exploring more adaptive and sophisticated forecasting techniques [26], [27], [28]. A more reliable forecasting method is essential for improving exchange rate prediction accuracy and mitigating risks arising from high volatility. A more precise model not only contributes to investment efficiency but also supports the development of more adaptive financial policies [29], [30], [31]. With a more accurate approach, economic decision-making can be carried out more optimally, making this study highly relevant in addressing current economic challenges [32], [33], [34].

This research is highly significant because exchange rate forecasting accuracy is crucial for economic players. More precise predictions help in financial risk management and the formulation of more efficient investment strategies [30], [35]. Additionally, more reliable forecasting results can serve as a foundation for economic policies that are more responsive to market dynamics [36], [37], [38].

Therefore, this study aims to develop a more accurate forecasting method for the Rupiah-to-Yen exchange rate. The primary objective is to achieve the lowest possible MAPE value by using a more advanced approach than previous models. By enhancing accuracy, this study is expected to provide better insights for economic decision-makers and contribute to improving the reliability of exchange rate forecasting in the future.

2. MATERIAL AND METHOD

2.1. Data

The data used in this study consisted of the latest exchange rate data for JPY/IDR, covering the period from March 21, 2022, to January 10, 2025, obtained from Investing.com. The dataset included 736 rows of daily exchange rate changes of the Rupiah against the Japanese Yen, recorded on business days (Monday to Friday).

2.2. Walk Forward Analysis Strategy

The WFA approach used in this study was the Expanding Window method, where, in each forward period, the model was trained using an increasing amount of historical data without removing previous data. Each time the period was updated, the exchange rate data increased by the number of business days in a week (Monday to Friday), reflecting a gradual data update. In this study, several periods were formed, as described in Table 1.

Table 1. Scenario Building with Walk Forward Analysis (WFA)

Scenario	Data Length	Amount of Data
Period 1	21 Maret 2022 – 29 November 2024	706
Period 2	21 Maret 2022 – 6 Desember 2024	711
Period 3	21 Maret 2022 – 13 Desember 2024	716
Period 4	21 Maret 2022 – 20 Desember 2024	721
Period 5	21 Maret 2022 – 27 Desember 2024	726
Period 6	21 Maret 2022 – 3 Januari 2025	731
Period 7	21 Maret 2022 – 10 Januari 2025	736

2.3. Data Preprocessing and Splitting

Data preprocessing was the preparation stage before building the model. This step was crucial in data management as it influenced the quality and accuracy of the final model results. The preprocessing steps used in this study included data normalization and sequence data structuring.

1) Data Normalization

This method transformed the scale while maintaining the relationship between the original values and the desired new scale [39]. MinMaxScaler performed data normalization by rescaling the original values into a range of [0,1] or another predefined range. The formula used for normalization with MinMaxScaler was as follows:

$$\tilde{z}_t = \frac{z_t - z_{min}}{z_{max} - z_{min}} \tag{1}$$

Where,

$\tilde{z}_t$: normalized value of the t-th data point (t = 1, 2, 3, …, n)

z_t : original value of the t-th data point (t = 1, 2, 3, …, n)

z_{max} : maximum value in the dataset before normalization

z_{min} : minimum value in the dataset before normalization

2) Sequence Data Structuring

The sequence length represented the amount of historical data used to form a single input sample. After the data was normalized, it was divided into sequences of length $\mathbf{\Lambda}$. If the dataset contained $\mathbf{\Psi}$ data points and the sequence length was $\mathbf{\Lambda}$, the number of sequences formed followed Equation (2):

$$n_\Omega = \mathbf{\Psi} - \mathbf{\Lambda} + 1 \tag{2}$$

The φ-th sequence consisted of data from φ to $\varphi + \mathbf{\Lambda} - 1$ within the normalized dataset, as shown in Equation (3). The dataset in sequence form was represented in Equation (4), where $\varphi = 1, 2, \ldots, n_\Omega$:

$$Z_\varphi = [z_{\tilde{\varphi}}, \tilde{z}_{\varphi+1}, \ldots, \tilde{z}_{\varphi\mathbf{\Lambda}-1}] \tag{3}$$

$$Z = \{Z_1, Z_2, \ldots, \tilde{Z}_{\mathbf{\Psi}\mathbf{\Lambda}+1}\} \tag{4}$$

Where the dataset dimensions were $(n_\Omega, \mathbf{\Lambda}, 1)$, with n_Ω as the number of sequences and $\mathbf{\Lambda}$ as the length of each sequence.

In this study, the dataset was divided into three subsets: training, validation, and testing data, with a proportion of 60:20:20. This ratio was commonly used to ensure that the validation and test data were sufficiently representative without compromising the amount of training data required for effective model learning [40].

2.4. Hybrid 1D-CNN-BiGRU Modeling

The workflow of the hybrid 1D-CNN-BiGRU model is shown in Figure 1.

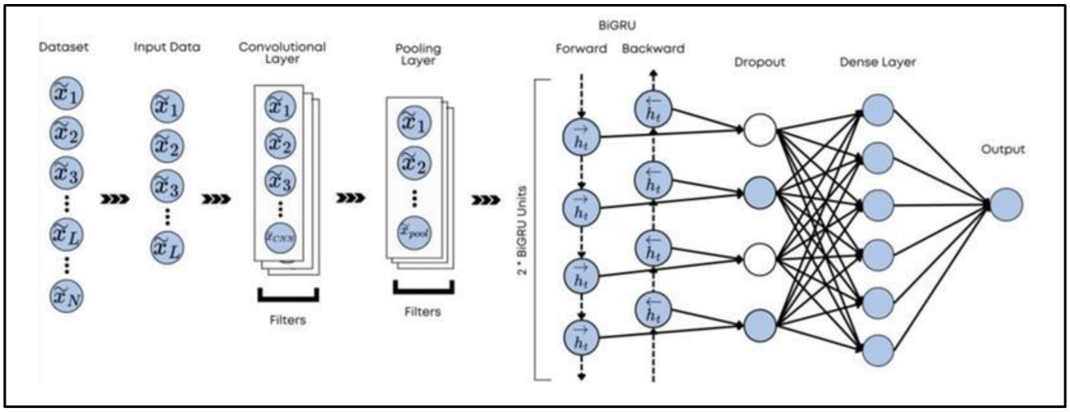


Figure 1. 1D-CNN-BiGRU Workflow

Figure 1 illustrated the Forward Propagation process in the 1D-CNN-BiGRU model using a single sequence simulation. In its implementation, the model processed sequential data simultaneously in batches, with the batch size being predefined. This process was then followed by Backward Propagation to update the model weights. The Forward Propagation stage included 1D-CNN modeling, BiGRU modeling, and hybrid 1D-CNN-BiGRU model formation.

2.4.1. 1D-Convolutional Neural Network (CNN) Modeling

CNN was employed for time series forecasting by leveraging a 1D convolutional layer. The parameters that governed the relationship between the input at a given time step and the neurons in the subsequent layer were represented as weights. The preprocessed input data was introduced into the 1D-CNN model, where the convolution operation was executed as formulated in Equation (5):

$$\hat{z}_{\rho}^{CNN}[m] = ReLU\left(\sum_{\tau=0}^{\kappa-1} \omega[\tau] \cdot \hat{z}_{\rho+m+\tau} + \beta_{\tau}\right) \tag{5}$$

In this equation, $ReLU(x)$ represents the Rectified Linear Unit activation function, which is mathematically defined as $\max(0,\ x)$. The variable $\hat{z}_{\rho}^{CNN}[m]$ denotes the convolution output at position m for sequence ρ . The kernel siee, which determines the receptive field of the convolution operation, is represented as κ. The weight of the filter at position τ is denoted by

$\omega[\tau]$, while the input data value at position $\rho + m + \tau$ is expressed as $\hat{z}_{\rho+m+\tau}$. Lastly, β_τ represents the convolutional bias, which helps adjust the influence of different features during learning.

2.4.2. Bidirectional Gated Recurrent Unit (BiGRU) Modeling

In BiGRU, data was processed at each time step. Since the data in this study was in sequence form, the CNN output entering the BiGRU had the dimension ($\tilde{x}_i$ pool, number of filters). The BiGRU model processed information using a gating mechanism designed to control the flow of information within the hidden state. The BiGRU model processed information using a gating mechanism designed to control the flow of information within the hidden state.

The Bidirectional Gated Recurrent Unit (BiGRU) was an architecture consisting of two GRUs. In the first pass, GRU was applied to the input sequence (forward layer). In the second pass, GRU was applied to the reverse sequence (backward layer). The BiGRU architecture is shown in Figure 2.

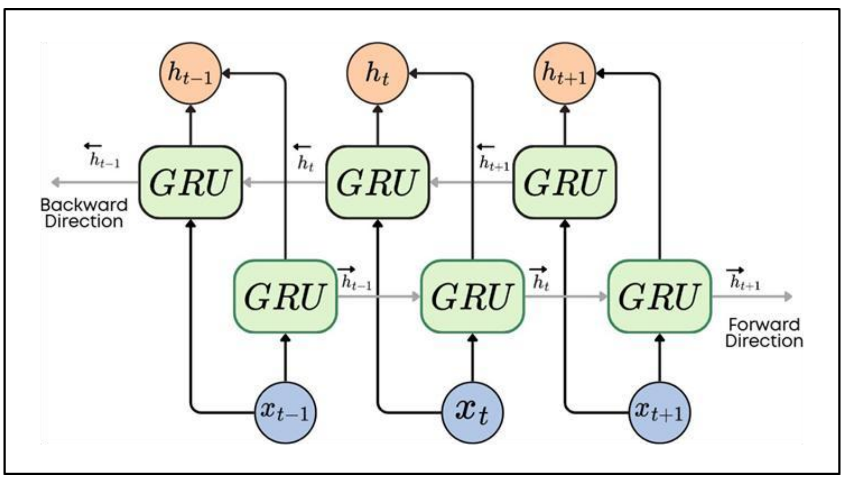


Figure 2. BiGRU Architecture Design

The BiGRU architecture, as illustrated in Figure 2, followed the same formulation as a standard GRU but conducted computations in both forward and backward directions. The mathematical representation of this process is given by the following equations:

$$\vec{s}_\tau = GRU_{fwd}\left(\tilde{v}_i^{pool}[\tau], \vec{s}_{\tau-1}\right), \tau = 1, \dots, \Theta \tag{6}$$

$$\overleftarrow{s}_\tau = GRU_{bwd}\left(\tilde{v}_i^{pool}[\tau], \overleftarrow{s}_{\tau-1}\right), \tau = 1, \dots, \Theta \tag{7}$$

$$s_\tau = concat(\vec{s}_\tau, \overleftarrow{s}_\tau), \tau = 1, \ldots, \Theta \tag{8}$$

In these equations, $\tilde{v}^{pool}$ represents the pooled input at time step τ. The forward hidden state at the previous time step is denoted by $\vec{s}_{\tau-1}$, while the backward hidden state at the next time step is represented as $\overleftarrow{s}_{\tau-1}$. The final hidden state after concatenation of the forward and backward states is expressed as s_τ, and Θ corresponds to the sequence length in the BiGRU process.

2.4.3. Hybrid 1D-CNN-BiGRU Model Formation

Once the input data passed through both the 1D-CNN and BiGRU layers, the final prediction output was generated in the output layer. The computation for this prediction is formulated in Equation (9):

$$\hat{\zeta} = \sum_{\iota=1}^{\delta} \nu_\iota \cdot \omega_\iota + \beta \tag{9}$$

In this equation, $\hat{\zeta}$ represents the predicted output value, while δ denotes the number of neurons in the preceding dense layer. The variables ν_ι and ω_ι refer to the input value and weight of the ι-th neuron, respectively. Lastly, β represents the bias added to the output.

2.5. Model Evaluation

The model's performance was assessed using the Mean Absolute Percentage Error (MAPE) as the evaluation metric, which is mathematically defined in Equation (10):

$$\text{MAPE} = \frac{1}{\Xi} \sum_{\tau=1}^{\Xi} \left| \frac{\chi_\tau - \hat{\chi}_\tau}{\chi_\tau} \right| \times 100\% \tag{10}$$

In this equation, Ξ represents the number of forecasted time points under evaluation. The actual observed value at time step τ is denoted as χ_τ, while the corresponding predicted value is represented as $\hat{\chi}_\tau$.

3. MAIN RESULTS

3.1. Development of Walk Forward Analysis Strategy

In this study, the Walk Forward Analysis (WFA) strategy with an Expanding Window approach was used to train the 1D-CNN-BiGRU model. Each period was updated by adding five additional working days (Monday-Friday) of historical data. Table 2 presented the data distribution for each dataset using the WFA strategy.

Table 2. Data Distribution for Each Period

Period	Total Data	Training Data	Validation Data	Test Data
1	706	420	140	136
2	711	423	141	137
3	716	426	142	138
4	721	429	143	139
5	726	432	144	140
6	731	435	145	141
7	736	438	146	142

3.2. Data Preprocessing

The preprocessing stage involved normalization and sequence data preparation. Table 3 compared the data before and after normalization.

Table 3. Data Normalization Comparison

Date	Original Value	Normalized Value
21/03/2022	120,00	1
22/03/2022	118,85	0,941327
23/03/2022	118,4	0,918367
24/03/2022	117,23	0,858673
25/03/2022	117,47	0,870918
⋮	⋮	⋮
10/01/2025	102,77	0,139796

In this study, the exchange rate of the Indonesian Rupiah (IDR) to the Japanese Yen (JPY) was transformed into a sequence dataset with a length of 5. This meant that each sequence contained five consecutive data points, representing exchange rates over the previous five working days, which were then used to predict the exchange rate for the following day.

3.3. Predictive Modelling

The CNN-BiGRU modeling was implemented using Python with the Keras TensorFlow library. Each hyperparameter combination in the grid search was evaluated based on the validation loss, which served as the primary metric. The best hyperparameter configuration was selected based on the lowest validation loss, indicating high prediction accuracy and strong generalieation capability for unseen data.

Table 4 displayed the hyperparameter candidates tested using grid search, with a total of 36 combinations. The model was trained for a maximum of 500 epochs, and each combination was trained using a batch siee of 4, meaning the training data was processed in small batches of 4 samples at a time.

Table 4. Hyperparameter Candidates

Hyperparameters	Candidate Values
CNN Filters	[64; 128; 256]
Kernel Siee	[2; 3]
BiGRU Units	[64; 128; 256]
Dropout Rate	[0,1; 0,2]
Learning Rate	[0,00001]

Based on Table 4, the model with the lowest validation loss was obtained using the following hyperparameter combination: 128 CNN Filters, Kernel Siee of 2, 256 BiGRU Units, and a Dropout Rate of 0.1. This model achieved a validation loss of 0.001103. Figure 3 displayed the training and validation loss graph for Period 1 using the best hyperparameter combination.

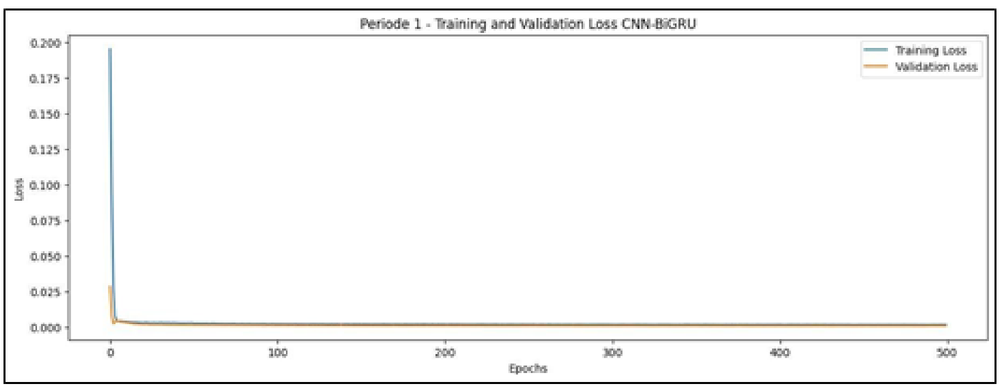


Figure 3. Loss Graph of the Best Model for Period 1

As seen in Figure 3, the validation loss closely followed the training loss, indicating that the model had strong generalization capability on unseen data.

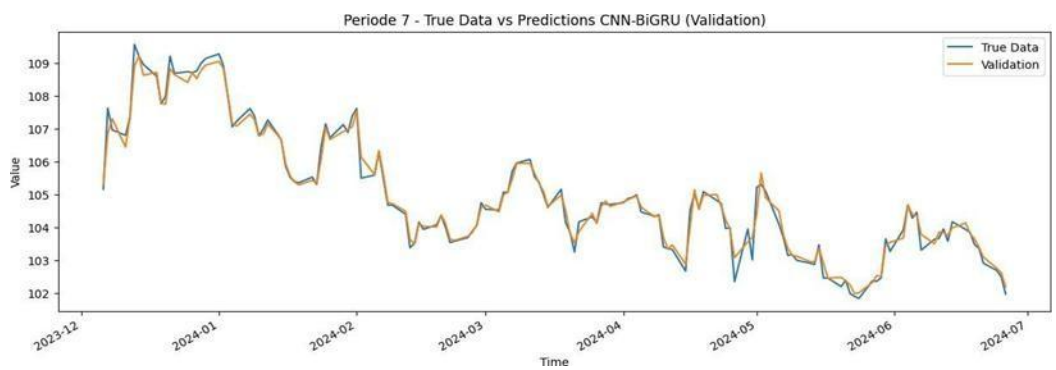
3.4. Model Evaluation

The model's performance was evaluated using the Mean Absolute Percentage Error (MAPE), with the results summarized in Table 5.

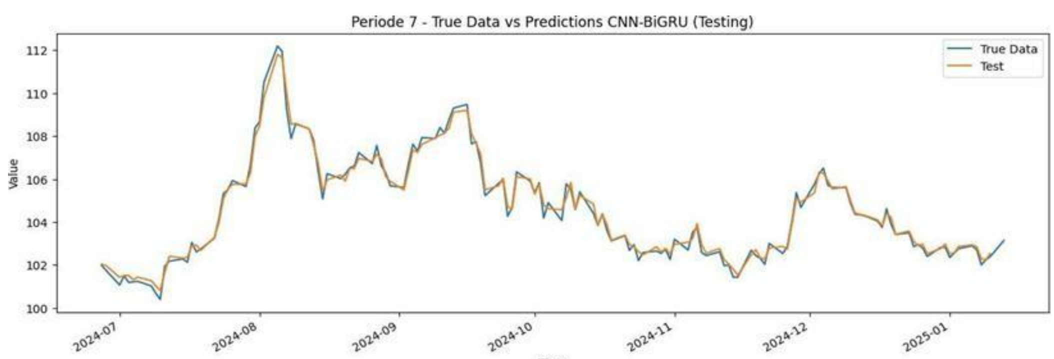
Table 5. Testing MAPE for Each Period

Testing Period	Testing MAPE (%)
24 May 2024 – 29 November 2024	0,576
30 May 2024 - 06 December 2024	0,576
5 June 2024 - 13 Descmber 2024	0,577
11 June 2024 - 20 December 2024	0,568
17 June 2024 - 27 December 2024	0,580
21 June 2024 – 03 January 2025	0,566
27 June 2024 – 10 January 2025	0,568

Table 5 showed that despite the increasing amount of training and testing data, the MAPE remained stable, indicating that the model maintained consistent prediction accuracy as more data was added. Figure 4 illustrated the comparison between actual values and predicted values for the validation and test datasets in Period 7.



(a)



(b)

Figure 4. Prediction Graph for Period 7 (a) validation data (b) test data.

Figure 4 demonstrated that the model, with its selected hyperparameters, closely followed the actual data, confirming its ability to generate accurate predictions even as new data was introduced.

3.5. Forecasting

At each step, the model was trained with the updated dataset and used to forecast the exchange rate of the Rupiah against the Japanese Yen for the next five-day period. The forecast results were presented in Table 6.

Table 6. Five-Day Forecast Results

Date	Forecasted Value	Actual Value
13 January 2025	102,992470	103,31
14 January 2025	103,173798	102,91
15 January 2025	103,126526	104,26
16 January 2025	103,266693	105,40
17 January 2025	103,252571	104,66

Based on Table 6, the forecasted values for 13–17 January 2025 ranged between Rp102.99 and Rp103.26, while the actual values varied between Rp102.91 and Rp105.40. The small differences between forecasted and actual values suggested that the model successfully captured the exchange rate trend with a high degree of accuracy.

Although some discrepancies existed between forecasted and actual values, they could have resulted from external factors such as global economic fluctuations, monetary policy changes, or market sentiment variability.

4. CONCLUSION

The Hybrid 1D-CNN-BiGRU model used in this study proves to be effective in capturing short- term volatility patterns and long-term trends in the exchange rate of the Indonesian Rupiah against the Japanese Yen, achieving high forecasting accuracy. This is demonstrated by the consistently low MAPE values, which remain below 1% in each testing period, indicating stability and reliability in predictions. The success of this model is supported by the implementation of the Walk Forward Analysis (WFA) strategy, which allows adaptation to historical data changes without disregarding past information, thereby enhancing the model's resilience in handling fluctuating market dynamics. Additionally, the selection of optimal parameters, such as the number of units in the GRU layer and the appropriate dropout rate, plays a crucial role in maintaining model efficiency, preventing overfitting, and ensuring good generalieation. Thus, this hybrid approach not only surpasses conventional methods but also maintains its performance over the long term, making it an effective solution for exchange rate forecasting.

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CONFLICT OF INTERESTS

The author(s) declare that there is no conflict of interests.

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