



## Integrasi CNN-Bi-LSTM dengan Attention Mechanism for rupiah exchange rate prediction

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### ABSTRACT

Exchange rates are a crucial indicator of a nation's economic stability. Fluctuations in exchange rates can influence investment decisions, international trade, and monetary policies. The prediction of foreign exchange rates against the Indonesian Rupiah holds significant importance in financial analysis and decision-making. Exchange rates are a crucial indicator of a nation's economic stability, influencing investment decisions, international trade, and monetary policies. However, accurately predicting foreign exchange rates remains a challenging problem due to the highly. This research aims to enhance prediction accuracy by proposing a CNN Bi-LSTM model with the addition of an Attention Mechanism (CNN Bi-LSTM AM). Historical exchange rate data were normalized and divided into training, testing, and validation sets. The CNN model extracts local features, BiLSTM captures bidirectional temporal patterns, and the Attention Mechanism highlights critical features to improve data processing efficiency. The evaluation was conducted using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) metrics. The results show that CNN Bi-LSTM AM outperformed BiLSTM and CNN Bi-LSTM, achieving MAPE values of 0.7795%, 0.3877%, 0.4062%, 0.7646%, 0.4267%, and RMSE values of 0.1953, 0.2199, 0.2069, 0.1758, 0.3250 for USD, Pounds, EURO, Yen, and Franc, respectively. The addition of the Attention Mechanism significantly contributed to improved accuracy, distinguishing this model from previous research. This study supports the relevance of innovation in hybrid architectures and Attention Mechanisms for financial time series predictions.

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### 1. INTRODUCTION

Exchange rates play a vital role in both global and domestic economies (Kiplangat, 2024). They are crucial for promoting international trade, attracting foreign investment, economic planning, monetary policy, risk mitigation, and affecting the prices of goods and inflation (Pamungkas et al., 2020). Changes in the rupiah's value relative to other currencies have a big effect on Indonesia's economic stability. (Anggraini, 2017).

Therefore, accurate predictions of rupiah exchange rate movements can help individuals, businesses, and the government make better decisions to foster economic growth (Sumargo & Wasito, 2024).

The instability of financial data, heavily influenced by macroeconomic factors and its non-linearity, makes predicting the rupiah exchange rate challenging (Utari, 2018). Exchange rate data is time-series in nature and exhibits complex patterns, necessitating robust methods to achieve accurate predictions (Qureshi et al., 2023). For time-series data, traditional statistical techniques like Autoregressive Integrated Moving Average (ARIMA) are frequently employed, but they frequently produce poor accuracy (ArunKumar et al., 2022). ARIMA is suitable for stationary data with seasonal patterns but is ineffective for nonlinear data and complex temporal dependencies in time-series data (Ardesfira et al., 2022). Deep learning techniques have been developed and used extensively in industries like healthcare and finance in recent years (Bustamam et al., 2022). The ability of deep learning methods to handle complex patterns and big data is a significant advantage, making them well-suited for time-series data.

Many studies have utilized deep learning methods to predict exchange rates, yet challenges remain in achieving high accuracy and addressing high market volatility (Casolaro et al., 2023). Long Short-Term Memory (LSTM) is a popular deep learning technique for time-series prediction (Liu et al., 2024). Several studies (Devi & Hendikawati, 2024) have shown that LSTM outperforms traditional statistical models in exchange rate prediction. However, LSTM has limitations in extracting spatial features and focusing on important features in the data, which can result in suboptimal models (Pangesti & Fahrurrozi, 2023).

An extension of LSTM that performs better in time-series prediction is called Bidirectional Long Short-Term Memory (Bi-LSTM) (Lstm & Dalam, 2024). Several studies have utilized a combination of Convolutional Neural Network (CNN) and Bi-LSTM for time-series prediction (Shakir Ali Ali et al., 2022). The CNN-BiLSTM model has successfully improved accuracy in financial data prediction but still has some limitations, requiring further development (Mushliha, 2024).

The main challenge lies in the complexity and non-linearity of exchange rate data, as well as the inability of existing models to fully capture the most critical features. CNN is efficient in extracting spatial features, and Bi-LSTM captures bidirectional temporal dependencies. However, these models often lack the capability to emphasize the most significant features within the data. According to previous studies, CNN-Bi-LSTM has limitations in emphasizing significant features (Marjani et al., 2024). This limitation reduces the interpretability and precision of predictions.

Research conducted in 2023 indicates that incorporating an Attention Mechanism (AM) into hybrid models can enhance both interpretability and accuracy (Zhang et al., 2023). This study proposes the development of a hybrid model based on CNN, Bi-LSTM, and AM for predicting the rupiah exchange rate. CNN is employed to extract spatial features from time-series data, while Bi-LSTM captures bidirectional temporal patterns (forward and backward). AM is integrated to focus more on significant features within the data. This study aims to develop a rupiah exchange rate prediction model based on CNN-BiLSTM-AM, capable of improving prediction accuracy by capturing spatial-temporal patterns and placing greater emphasis on significant features in the data. This model is expected to contribute to the development of more reliable prediction systems and provide new insights for market participants and policymakers in understanding exchange rate dynamics and making better-informed decisions based on the generated predictions.

## 2. RESEARCH METHOD

The research begins with data collection from Yahoo Finance, focusing on the exchange rates of five major foreign currencies against the Indonesian Rupiah. The collected data undergoes preprocessing, which involves splitting it into training, testing, and validation datasets, normalizing the data using Min-Max normalization, and creating time steps for time series forecasting. Following preprocessing, three models—BiLSTM, CNN-BiLSTM, and CNN-BiLSTM-AM—are developed. The models are then evaluated using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) metrics. The performance of each model is assessed, and the best-performing model is selected based on the smallest RMSE and MAPE values.

### 2.1. Data Collection

The research utilizes exchange rate data for five major foreign currencies (USD, EUR, GBP, JPY, and CHF) against the IDR, sourced from Yahoo Finance. The data spans the period from January 2, 2024, to December 28, 2024, yielding 259 entries per currency and a total of 1,295 data points. These currencies were chosen due to their significant impact on the Indonesian Rupiah.

### 2.2. Data Preprocessing

After obtaining the data from Yahoo Finance, it was divided into training, testing, and validation datasets. Eighty percent of the data, comprising 207 entries, was used for training the model. Ten percent, consisting of 27 entries, was used for testing, and the remaining 25 entries were used for model validation.

The next step is data normalization, which is used to help the model generalize better. The normalization method applied in this research is Min-Max Normalization, where the data is mapped to a range between zero and one. The normalization formula is as follows:

$$x_{norm,i} = \frac{x_i - x_{min}}{x_{maks} - x_{min}} \quad i = 1, 2, 3, \dots, n \quad (1)$$

$x_{norm}$  represents the normalized data,  $x_{maks}$  is the highest value in the dataset, and  $x_{min}$  is the lowest value in the dataset (Yang & Wang, 2021).

For time-series data, time steps are used to predict future data points. Time steps refer to the number of previous data points used to forecast the next value. In this research, a time step of five is utilized, meaning the model uses the five preceding data points to predict the upcoming value.

### 2.3. Model Implementation

#### a. Bidirectional Long Short-Term Memory (BiLSTM) Model

BiLSTM is a time-based recurrent neural network that operates in both directions. It efficiently captures the inherent relationships between present, past, and future data by utilizing forward and backward time series training, thereby optimizing the use of data information (Varadharajan & Nallasamy, 2022).

The BiLSTM network is an improved and optimized version of the LSTM network, designed to address the technical issues in LSTM caused by one-way propagation. LSTM has a memory cell and three gate structures: the Forget Gate ( $f_t$ ), Input Gate ( $i_t$ ), and Output Gate ( $o_t$ ) (Yang & Wang, 2021). In time series predictions, the one-way propagation of LSTM limits its ability to leverage both past and future time sequence information to assess the current state.

The BiLSTM network is designed by combining two LSTM networks, creating a forward propagation hidden layer and a backward propagation hidden layer. This architecture allows data to flow both from the past to the future and from the future to

the past, enabling the output at the current time step to incorporate information from both directions simultaneously.

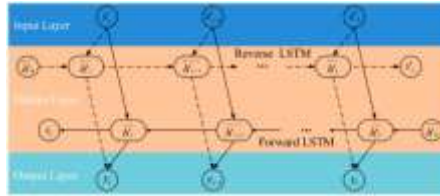


Figure 1. The Structure of the BiLSTM Neural Network (Zhu et al., 2024)

Figure 1 depicts the BiLSTM model's output unfolded along the time axis, where  $x'$  denotes the input to the model,  $h'$  represents the hidden layer state, and  $y$  is the model's output. Assuming that the forward and backward propagation hidden layer states at time  $t$  are represented by  $\overrightarrow{h'_t}$  and  $\overleftarrow{h'_t}$  respectively, then:

$$\overrightarrow{h'_t} = LSTM(x'_t, \overrightarrow{h'_{t-1}}) \quad (2)$$

$$\overleftarrow{h'_t} = LSTM(x'_t, \overleftarrow{h'_{t-1}}) \quad (3)$$

Where LSTM refers to the LSTM unit,  $x'_t$  is the input at time  $t$ ,  $\overrightarrow{h'_{t-1}}$  and  $\overleftarrow{h'_{t-1}}$  are the forward and backward propagation hidden layer states at time  $t - 1$ , respectively. The overall state output  $y_t$  of the BiLSTM network is generated by combining  $\overrightarrow{h'_t}$  and  $\overleftarrow{h'_t}$  (Zhu et al., 2024).

#### b. CNN-BiLSTM Model

CNN-BiLSTM is a hybrid model that integrates the advantages of Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) (Nguyen & Ha, 2024). CNN serves as a feature extractor, excelling at capturing local patterns and spatial features in the data. It processes time series data by extracting significant features from the input data through convolution operations. BiLSTM then processes the output from CNN to capture temporal relationships from both the past (backward sequence) and the future (forward sequence), effectively analyzing long-term time dependencies (Staffini, 2023).

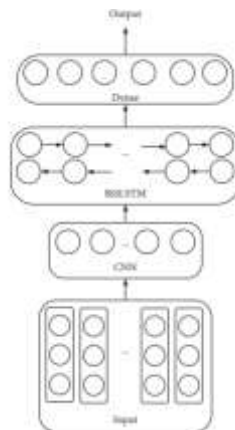


Figure 2. The Structure of CNN-BiLSTM (Mushliha, 2024)

#### c. The CNN-BiLSTM AM Model

The Attention Mechanism (AM) is inspired by research on human vision (Niu et al., 2021). Traditional neural networks are unable to distinguish the significance of different signals when processing information (Barrett et al., 2019). In contrast, the Attention Mechanism (AM) assigns varying weights based on specific features (Chen &

Shi, 2021). The Attention Mechanism (AM) assigns higher weights to important information while disregarding less relevant data (Zhang et al., 2023).

This aims to improve the efficiency of information processing by assigning focused weights, while also addressing the issue of information loss caused by long sequences in LSTM (Zhang et al., 2023). Therefore, the addition of AM can further enhance the accuracy of exchange rate prediction.

As previously mentioned, CNN-BiLSTM has a limitation in that it does not focus on important features in the data. Adding the Attention Mechanism (AM) to CNN-BiLSTM is expected to address this limitation and improve accuracy. In this study, the CNN-BiLSTM AM model is developed through the following steps: (a) Step 1: Perform data preprocessing. (b) Step 2: A CNN-BiLSTM AM model flow diagram is shown in Figure 3. The CNN layer is used to extract internal features from the data, which consists of Conv1D convolution followed by a pooling layer. In order to capture patterns of internal dynamic changes, the CNN applies the BiLSTM layer to the local features extracted by the CNN. The Attention Mechanism (AM) then applies the BiLSTM layer to automatically assign different weights to the features extracted by the CNN, allowing for a deeper exploration of temporal correlations. Step 3: To get the desired values, normalize the prediction results.

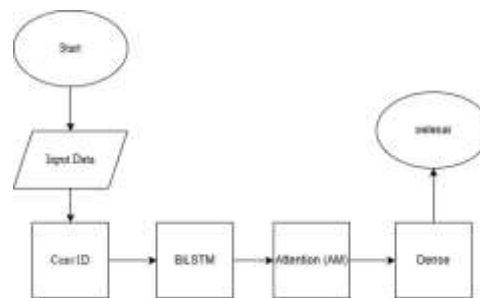


Figure 3. The structure of the CNN-BiLSTM AM model

#### d. Model Evaluation

After implementing the BiLSTM, CNN-BiLSTM, and CNN-BiLSTM AM methods, model evaluation is required to compare the performance of the resulting models. This evaluation is commonly used in prediction or regression models to measure how well the model predicts actual data (Staffini, 2023). The evaluation metrics employed are Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). RMSE is calculated by taking the square root of the average of the squared differences between the actual and predicted values.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (4)$$

MAPE is an evaluation metric that assesses the accuracy of a prediction model by calculating the average percentage difference between the actual and predicted values.

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100 \quad (5)$$

Where  $y_i$  is the actual value,  $N$  represents the number of data points, and  $\hat{y}_i$  is the predicted value. The MAPE results can be interpreted based on the Lewis scale. The Lewis scale classifies the accuracy of the prediction results as follows:

Table 1. MAPE Classification

MAPE Value	Interpretation
$MAPE \geq 50\%$	Inaccurate
$20\% \leq MAPE < 50\%$	Normal
$10\% \leq MAPE < 20\%$	Good
$MAPE < 10\%$	Very Accurate

Source: (Pangesti & Fahrurrozi, 2023)

Through this scale, we can determine how well the performance of the prediction model is based on the MAPE value. The smaller the RMSE and MAPE values, the more accurate the resulting prediction model.

### 3. RESULTS AND DISCUSSION

This study uses historical foreign exchange rates against the Indonesian Rupiah obtained from Yahoo Finance to predict future exchange rates. Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) are evaluation metrics used to compare the CNN Bi-LSTM with AM (CNN Bi-LSTM AM) model to two other models, namely Bi-LSTM and CNN Bi-LSTM. The data used has been normalized, then structured into time steps and divided into 80% training data, 10% testing data, and the remaining data for validation.

The BiLSTM model is obtained by using the best parameters for the first and second BiLSTM layers (Bidirectional(LSTM(25) and Dense(10)), with ReLU activation and the Adam optimizer with a learning rate of 0.001. During model training, the early stopping technique is also used to avoid overfitting. In the CNN-BiLSTM model, the same parameters are used for the BiLSTM part, but a Conv1D layer is added with a filter size of 3 and kernel size of 3, using ReLU activation, followed by MaxPooling 1D with a pool size of 2. In the CNN-BiLSTM AM model, the same parameters are used for the CNN-BiLSTM part, but an Attention Layer with sigmoid activation is added. The performance results of each model can be seen in Table 2.

Table 2. Parameters and Results of the Models

Prediction Model	Currency	Parameters			RMSE	MAPE
		Time steps	epoch	batch		
BiLSTM	USD	5	25	20	0.2062	0.8378%
	Pound sterling	5	29	20	0.2645	0.5056%
	EURO	5	21	20	0.3084	0.6731%
	Yen	5	23	20	0.2229	0.9679%
	Franc	5	37	20	0.3024	0.4874%
CNN-BiLSTM	USD	5	25	20	0.1998	0.7950%
	Pound sterling	5	50	20	0.2582	0.4704%
	EURO	5	20	20	0.1866	0.4132%
	Yen	5	26	20	0.1909	0.8052%
	Franc	5	60	20	0.3090	0.4666%
CNN-BiLSTM AM	USD	5	21	20	0.1953	0.7795%
	Pound sterling	5	44	20	0.2199	0.3877%
	EURO	5	41	20	0.2069	0.4062%
	Yen	5	29	20	0.1758	0.7646%
	Franc	5	50	20	0.3250	0.4267%

Table 2 shows that the best performance for each foreign exchange rate against the Rupiah is achieved by the CNN-BiLSTM model, followed by the CNN-BiLSTM model in second place, and then BiLSTM. Based on the Lewis scale, the MAPE values of all models fall into the "very accurate" category, as they are below 10%.

The Bi-LSTM model effectively captures bidirectional temporal patterns in time-series data, which are critical for understanding exchange rate dynamics. However, it lacks the ability to extract spatial features, such as short-term trends or local patterns. The CNN-BiLSTM model addresses this limitation by incorporating CNN layers to extract spatial features, which enhances prediction performance. Despite this improvement, the CNN-BiLSTM model struggles to focus on the most relevant features in the data, limiting its accuracy.

The integration of the Attention Mechanism in the CNN-BiLSTM-AM model overcomes this limitation by enabling the model to assign higher weights to significant features. This allows the model to prioritize critical temporal and spatial patterns, leading to more accurate predictions. The results suggest that the Attention Mechanism enhances the interpretability and performance of the hybrid model, particularly for complex and volatile time-series data such as exchange rates.



Figure 4. Chart of Comparison Between The Predicted and Actual Exchange Rates of USD to IDR

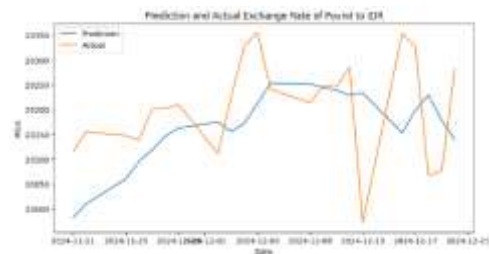


Figure 5. Chart of Comparison Between The Predicted and Actual Exchange Rates of Pound to IDR



Figure 6. Chart of Comparison Between The Predicted and Actual Exchange Rates of EURO to IDR

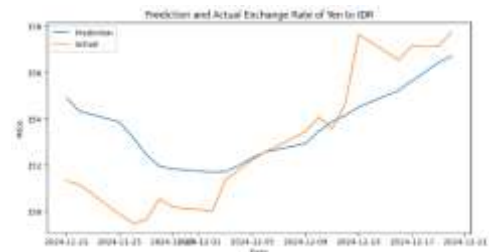


Figure 7. Chart of Comparison Between The Predicted and Actual Exchange Rates of Yen to IDR



Figure 8. Chart of Comparison Between The Predicted and Actual Exchange Rates of Franc to IDR

Figures 4, 5, 6, 7, and 8 present the visualization results of various currencies' values against the rupiah, predicted using the CNN-BiLSTM AM model. These

visualizations reveal that the CNN-BiLSTM-AM model effectively captures fluctuations in exchange rates over time, demonstrating its ability to model the volatile nature of currency markets. The close alignment between predicted and actual values underscores the robustness of the proposed model.

The findings of this study align with previous research emphasizing the effectiveness of combining CNN and Bi-LSTM for time-series prediction (Mushliha, 2024). CNN excels at extracting local features, while Bi-LSTM captures long-term dependencies. Additionally, incorporating the Attention Mechanism further enhances the model's ability to focus on important features, as noted in (Zhang et al., 2023). This study refines the CNN-BiLSTM architecture by integrating AM, demonstrating its potential to improve financial predictions and address challenges posed by nonlinear and volatile exchange rate data.

#### 4. CONCLUSION

The findings of this study show that the CNN-BiLSTM-AM model significantly outperforms the BiLSTM and CNN-BiLSTM models in predicting the Indonesian Rupiah exchange rate, as evidenced by the lower MAPE and RMSE values. This superior performance is attributed to the integration of Attention Mechanism (AM), which enhances the model's ability to prioritize important features, effectively overcoming the complexity and nonlinearity of exchange rate time series data. By combining CNN for spatial feature extraction, Bi-LSTM to capture bidirectional temporal patterns, and AM to emphasize significant data points, the proposed hybrid architecture provides a powerful and accurate prediction tool. These results underscore the potential of the CNN-BiLSTM-AM model to support data-driven decision-making for policy makers, businesses, and financial analysts. Moreover, its adaptability makes it a promising solution for broader financial applications, such as stock market prediction and economic forecasting, which paves the way for future research and advancements in financial time series analysis.

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