Syntax Literate: Jurnal Ilmiah Indonesia p–ISSN: 2541-0849
e-ISSN: 2548-1398
Vol. 10, No. 1, January 2025

RUPIAH EXCHANGE RATE PREDICTION WITH LONG SHORT-TERM MEMORY ALGORITHM

Ayu Poernomo
Universitas Indonesia, Indonesia
Email: ayupoernomo@gmail.com

Abstract

The fluctuation of the Rupiah exchange rate against foreign currencies in Asia presents a significant challenge in maintaining Indonesia's economic stability. This study aims to forecast Rupiah exchange rates using the Long Short-Term Memory (LSTM) algorithm. Weekly exchange rate data from 2020 to 2024 were analyzed using a machine learning approach. The process involved data normalization, model training, and evaluation using Mean Absolute Per- centage Error (MAPE) and R-Squared. The results indicate that the LSTM model effectively captures non-linear patterns in time series data with high accuracy. This model implementation provides valuable insights for financial decision-makers, regulators, and academics in understanding the dynamics of foreign exchange markets.

Keywords: Rupiah Exchange Rate, Long Short-Term Memory, Machine Learning, Mean Absolute Percentage Error, R-Squared

Introduction

The rupiah exchange rate plays a very important role in maintaining the stability of the Indonesian economy. As one of the macroeconomic indicators, exchange rate movements not only reflect the fundamental conditions of the domestic economy but also show the complex interaction between monetary policy, international trade, and global market dynamics. The high exchange rate is a major concern, especially for developing countries such as Indonesia because of its potential wide impact on economic stability, international trade, and foreign investment flows (Alekseeva et al., 2021; Montaño Moreno et al., 2013; Rustam et al., 2021). Uncontrolled exchange rate volatility can create economic uncertainty, hinder business planning, and trigger pressure on the monetary and fiscal sectors (Ibrahim et al., 2024).

The COVID-19 pandemic has had a significant impact on the movement of the rupiah exchange rate. At the beginning of the pandemic, travel restrictions, global supply chain disruptions, and reduced trade activity led to a decline in demand for foreign exchange (Lee et al., 2019; Li, 2016). Ibrahim et al. (2024) noted that *spillover volatility* had decreased due to the cessation of global market activity, but then experienced a sharp increase due to market panic. In addition, the reduction in exports and imports during the pandemic has also exacerbated exchange rate instability.

In addition to the pandemic, exchange rate instability is also affected by global geopolitical events, such as the Russia-Ukraine conflict. The conflict caused major disruptions to energy supplies, pushing crude oil prices to historic highs. The impact is not only felt on the energy sector but also on the foreign exchange market (Clark & Newbury, 1952; de Myttenaere et al., 2016). Oil price fluctuations directly affect exchange rates through various channels, such as international trade, portfolio allocation, and market uncertainty (Zhao et al., 2023).

In the Asian region, the foreign exchange market is known to have complex dynamics and high interdependence. Liu et al. (2023) emphasized the importance of exchange rate prediction, especially against benchmark currencies such as the Dollar

The United States (USD), given its significant impact on the stability of the regional economy. However, the unique characteristics of Asian markets—such as differences in monetary policy, the influence of market sentiment, and fluctuations in commodity prices—make exchange rate predictions challenging (Asesh, 2022; Brownlee, 2017).

Foreign exchange rate prediction is one of the main challenges in the financial sector. The foreign exchange market is the largest market in the world, with a daily transaction value of more than USD7.5 trillion (McGuire et al., 2022). However, the efficient nature of the market that new information is quickly reflected in prices makes it difficult to predict exchange rate movements accurately. Traditional statistical models such as *Autore- gressive* (*AR), Moving Average* (*MA*), and *Autoregressive Integrated Moving Average* (*ARIMA*) are often used to predict exchange rates. However, these models have limitations in capturing non-linear patterns and data complexity.

Sudden changes due to unforeseen events, such as global financial crises or pandemics, are often not well predicted by traditional statistical models. In addition, the use of multi-dimensional data, such as monetary policy, market sentiment, and commodity prices, is increasingly challenging for traditional methods due to their limitations in processing large amounts of data and complex non-linear relationships.

Along with the increasing complexity of data, machine *learning methods* have begun to be used in predicting exchange rates. One of the most prominent methods is *Long Short-Term Memory* (*LSTM*), which is part of a *neural network*. *LSTMs* are designed to handle long-time series data, with the ability to remember long-term patterns and capture non-linear relationships in the data.

Previous research has shown that *LSTM* can provide more accurate data than traditional models. A study that combines *CNNs* with *LSTM* to predict foreign exchange market trends, produces higher accuracy than its la- in approach (Xueling et al., 2023). Other research noted that *LSTM* is very effective in handling time series data, especially in capturing complex and non-linear patterns that cannot be handled well by *the ARIMA* model (Mao et al., 2024).

Most previous studies have focused on major currency pairs (e.g., USD/EUR, USD/JPY), while studies that specifically analyze Rupiah exchange rate predictions are still limited. Based on the description above, this study aims to develop a Rupiah exchange rate prediction model in the Asian region using *the LSTM* algorithm. This model is expected to help foreign exchange market participants make more informed decisions and improve rupiah exchange rate stability.

Currency exchange rate fluctuations, particularly in the Asian foreign exchange market, are influenced by complex economic, political, and market dynamics. Based on the Efficient Market Hypothesis (EMH), currency prices reflect all available market information, including monetary policy, geopolitical events, and global sentiment (Ibrahim et al., 2024). However, the unique characteristics of Asian markets, such as differences in economic policies between countries and the influence of commodity prices, make it difficult to predict exchange rates (Liu et al., 2023). In the face of these challenges, Long Short-Term Memory (LSTM) technology is becoming an increasingly popular prediction method due to its ability to capture non-linear patterns in time series data, which is difficult to capture by traditional methods such as ARIMA (Liu et al., 2023). With the ability of LSTM to study long-term data patterns and adjust to market volatility, this study aims to apply LSTM in predicting exchange rates and evaluating their accuracy using Mean Absolute Percentage Error (MAPE) and R-Squared.

The main objective of this study is to apply the LSTM algorithm to predict foreign exchange rates and evaluate the results using MAPE and R-Squared. The research is limited to foreign exchange rate data in Asia from 2020 to 2024. The results of the study are expected to provide benefits for investors in reducing the risk of losses due to foreign exchange fluctuations, adding academic literature related to the implementation of LSTM, and supporting regulators in understanding foreign exchange market conditions for better policymaking.

Research Methods

This study uses a predictive design of data exploration by utilizing secondary data in the form of currency exchange rates in Asia from January 2020 to September 2024. Data is collected through the Real-Time Finance Data API, which generates files in JSON format for easy processing. After the data is obtained, the preparation process includes sorting, handling lost data with the Last Observation Carry Forward (LOCF) method, sharing training and test data with an 80:20 ratio, and normalizing using MinMaxScaler. The prediction model is built using the Long Short-Term Memory (LSTM) algorithm via the Hard library in Python, with Adam's optimization algorithm to improve learning efficiency. The model evaluation was carried out with Mean Absolute Percentage Error (MAPE) and R-squared metrics, where predictions were scored based on the level of accuracy, ranging from inaccurate (MAPE > 50) to very accurate (MAPE < 10). The results of this evaluation are expected to provide a solid basis for reliably predicting currency exchange rates and support decision-making.

Results and Discussion

A. Exchange Rate Projections

The data used in this study is the exchange rate of countries in Asia against the Rupiah. Data was obtained through *the Real-Time Finance Data API* with a time period from 2020 to 2024. The price data used is weekly data. The country names and currency codes are presented in Table 2. An example of exchange rate price data obtained is presented in Table 2.

Table 1. YER/IDR Exchange Rate Price Data

Date	Exchange Rate Price
1/3/2020	55.6177
1/10/2020	55.553
-	-
1/24/2020	54.3967
.	.
.	.
.	.
13/09/2020	61.5448

Source: Researcher (2024)

The data obtained in one country is 249 data. Thus, the total data from 24 countries is 5,976 data. In this data, *missing data* is checked. It is known that there is some missing data so it needs to be substituted using *Last Obervation Carry Forward* (*LO-CF).* The results of the substitution can be seen in Figure 1. The figure shows the results of the YER/IDR exchange rate price data plot in full. The orange color plot shows the original data, while the blue color indicates the data that was filled in to cover the blanks. The empty data is filled with the ffill command that is already available in the Pandas library.

In the next stage, the LSTM model is used to predict the exchange rate price in the next one, seven, and 30 days. The LSTM model used consists of two layers, each with 50 units. In addition, this model also uses one dense unit for output, which serves to produce the final result of the prediction. The optimizer used is Adam, which is one of the popular optimization algorithms in deep learning models because of its ability to accelerate convergence and solve learning problems. The training process was carried out for 50 epochs with a batch size of 32, which was considered sufficient for this model to achieve stable convergence.

Table 2. Country Names and Currency Codes in Asia

No.	Country	Currency Code
1.	Bahrain	BHD
2.	Bangladesh	BDT
3.	Bhutan	BTN
4.	Brunei	BND
5.	Cambodia	KHR
6.	Cyprus	EUR
7.	Israel	THEY
8.	Jordan	IODINE
9.	Kuwait	KWD
10.	Laos	LAK
11.	Lebanon	LBP
12.	Macau	MOP
13.	Nepal	NPR
14.	Oman	OMR
15.	Pakistan	PKR
16.	Qatar	QAR
17.	Saudi Arabia	SAR
18.	Sri Lanka	LKR
19.	Tajikistan	TJS
20.	Turkey	TRY
21.	Turkmenistan	TMT
22.	United Arab Emirates	AED
23.	Uzbekistan	UZS
24.	Yemen	LOCATION

Source: Researcher (2024)

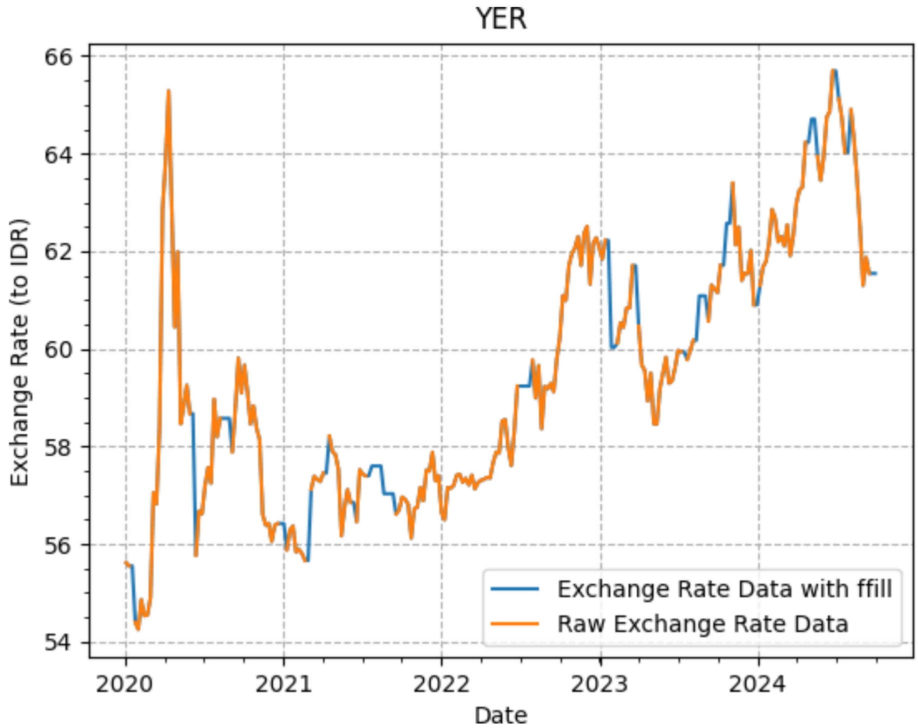

Figure 1. YER/IDR exchange rate price data plot)
Source: Researcher (2024)

The prediction results for one, seven, and the next 30 days are presented in Figure 2.. This chart shows two lines: the blue line representing the actual exchange rate price, and the orange line showing the predicted results of the *LSTM* model. In addition, yellow, green, and purple colors show prediction results for one, seven, and 30 days ahead, respectively.

The prediction results show that *the LSTM* model can predict the price movements of the exchange rate with a high degree of accuracy, especially for short-term predictions (one and seven days). However, for long-term predictions (30 days), the accuracy decreases slightly, which may be due to higher uncertainty and greater fluctuations over longer time periods.

Overall, the results obtained show that the LSTM model can be used effectively to predict exchange rate prices in the short term, although there are still challenges in predicting more complex long-term movements. These results can be used as a basis for future research that explores various other modeling techniques or more optimal parameter settings to improve long-term prediction accuracy.

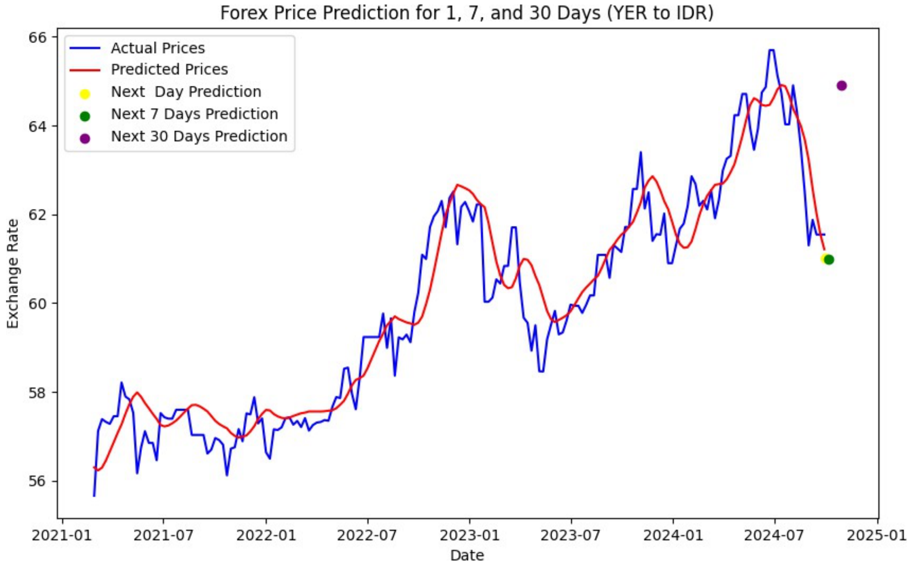

Figure 2. Prediction Results Using *LSTM*
Source: Researcher (2024)

B. Evaluation of *LSTM Models*

The performance of *the LSTM* model was calculated using MAPE measurements with ha- sil as presented in Table 3. The table provides a comparison of the performance of *the LSTM* model at various numbers *n*. The total number of samples successfully modeled was 24.

Based on the results of the *MAPE calculation*, both the sum n = 1, *n = 7, and n* = 30 have the majority of accurate results. A total of 23 out of 24 samples were included in the very accurate category with *MAPE* results of 0-10. Meanwhile, there was one sample that had *a MAPE* result of more than 50 (inaccurate) for every n number, namely in Lebanon.

Table 3. LSTM Model Performance

MAPE		Number n		
Range	**Limbs**	**1**	**7**	**30**
0-10	Highly accurate	26	26	26
11-20	Good	0	0	0
21-50	Reasonable	0	0	0
>50	Inaccurate	1	1	1

Source: Researcher (2024)

In addition to using *MAPE*, the evaluation was carried out by calculating *R-Squared*. Details of the evaluation results are presented in Table 3. *MAPE* is used to measure the performance of the model, while *R-Squared* is used to assess whether the predictor variable can explain the relationships in the model well. A high *R-Squared* value indicates that the model can explain the variability of the data well.

Table 4. *MAPE* and *R-Squared Values*

No.	Country	Code Eye	MAPE Values			*R-Squared* (%)
			n=1	*n=7*	*n=30*	
1.	Bahrain	BHD	1.33	2.30	4.71	0.2563
2.	Bangladesh	BDT	0.35	0.23	2.67	1.3751
3.	Bhutan	BTN	0.50	0.79	2.31	0.9185
4.	Brunei	BND	0.74	1.38	4.34	1.0152
5.	Cambodia	KHR	1.09	1.63	5.15	0.9985
6.	Cyprus	EUR	0.50	0.92	3.71	1.2655
7.	Israel	THEY	0.99	1.54	8.32	1.2013
8.	Jordan	IODINE	0.70	1.02	5.27	3.1140
9.	Kuwait	KWD	0.79	1.61	4.61	0.7883
10.	Laos	LAK	0.49	0.56	1.07	0.6217
11.	Lebanon	LBP	77.20	95.91	221.95	4.2007
12.	Macau	MOP	0.42	0.68	4.98	4.9610
13.	Nepal	NPR	0.49	0.55	4.65	1.1742
14.	Oman	OMR	1.87	3.48	4.46	0.4305
15.	Pakistan	PKR	1.01	1.64	3.52	0.7962
16.	Qatar	QAR	0.87	1.40	2.81	3.3625
17.	Saudi Arabia	SAR	0.34	0.45	3.76	2.4436
18.	Sri Lanka	LKR	1.12	2.88	6.50	6.2600
19.	Tajikistan	TJS	0.12	0.37	3.92	2.1054
20.	Turkey	TRY	1.65	2.16	5.81	5.7840
21.	Turkmenistan	TMT	0.54	1.49	1.39	0.5307
22.	UAE	AED	0.73	1.34	4.11	0.3707
23.	Uzbekistan	UZS	0.11	0.15	1.44	0.8792
24.	Yemen	LOCATION	1.26	2.58	4.15	2.0677

Source: Researcher (2024)

C. Discussion of Research Results

The results show that the *Long Short-Term Memory* (*LS-TM*) model has an excellent performance in predicting the exchange rate of the Ru- piah against Asian currencies, especially for short-term predictions. Based on the evaluation using *the Mean Absolute Percentage Error* (*MA-PE),* as many as 23 out of 24 samples analyzed had a very high level of accuracy (*MAPE* < 10%). This indicates that *LSTMs* are able to capture short-term patterns well, in accordance with the findings of Mao et al. (2024), which also show the superiority of LSTMs in modeling complex and nonlinear time series data.

However, on long-term predictions (the next 30 days), the model's accuracy declined with one sample (Lebanon) showing *MAPE* above 50%, which was categorised as inaccurate. This decline can be explained by the volatility of exchange rate data that tends to increase over a longer period, as well as the reliance on historical data that may not reflect sudden market changes. Zhao et al. (2023) also noted that the *LSTM* model has limitations when used to predict exchange rate risk in highly volatile situations, such as the impact of geopolitical conflicts.

The process of filling in lost data using the *Last Observation Carry Forward* (*LOCF*) method has proven to be effective in maintaining data continuity without significantly affecting model performance. However, this method has limitations in dealing with very dynamic data patterns, so it is an area that needs to be improved in further research. For example, Mao et al. (2024) suggest the use of data decomposition methods to improve the quality of model inputs.

In practical terms, the results of this study make a significant contribution to foreign exchange market participants and policymakers. Accurate long-term predictions can help investors make more timely decisions, while regulators can use this model to monitor market risks more proactively. However, for long-term applications, the development of a hybrid model that combines LS-TM with other approaches, such as *Transformer* or *Attention Mechanism*, as proposed by Liu et al. (2023).

This study also shows that machine learning-based prediction models are highly dependent on the quality of input data. Therefore, steps such as data normalization, selection of relevant features, and handling of missing data are critical to ensure optimal model performance. With these results, future research can focus on exploring more optimal model parameters or incorporating additional features, such as market sentiment data or macroeconomic indicators, to improve prediction accuracy.

Conclusion

Based on the results obtained from this study, it can be drawn that the Long Short-Term Memory (LSTM) model is effective in predicting the currency exchange rate against the Rupiah, especially for short periods such as 1 to 7 days, with a high level of accuracy based on evaluation using Mean Absolute Percentage Error (MAPE). As many as 96% of the sample had a MAPE below 10%, indicating a very accurate prediction, except in the case of the Lebanese currency which showed extreme fluctuations. However, the model's performance declined on long-term predictions (30 days) due to high market volatility. The study also shows that the LSTM model relies heavily on historical data, making it less able to capture sudden changes or external factors such as government policies and geopolitical events. For the future, the research suggests the development of a hybrid model that combines LSTM with other methods such as ARIMA, the utilization of macroeconomic data and market sentiment to improve accuracy, and the application of Explainable AI (XAI) to improve the interpretability of the model. Regulators, investors, and academics are expected to leverage this model for better data-driven decision-making, while still being mindful of the model's limitations in handling highly dynamic and highly volatile data.

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