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Research article

Deep Learning Approach for USD to IDR Forecasting with LSTM

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ABSTRACT

This Research explores the use of Long Short-Term Memory (LSTM) networks for forecasting the USD to IDR exchange rate, with the goal of improving prediction accuracy in the volatile foreign exchange market. By leveraging historical data, including daily exchange rates and trading volume, the LSTM model captures long-term dependencies and patterns within the time series data. The results show that the LSTM model effectively predicts general trends and medium-term fluctuations, demonstrating its capacity to follow market dynamics. However, the model struggles with extreme volatility and sudden market shifts, particularly during unforeseen geopolitical or economic events. This limitation highlights the need for further enhancement through the incorporation of additional features, such as macroeconomic indicators, sentiment analysis, and real-time news data. Furthermore, the study suggests the potential benefits of combining LSTM with other machine learning techniques to create hybrid models that can better handle short-term fluctuations and extreme events. In conclusion, while LSTM shows promise for exchange rate forecasting, its performance can be improved by refining model parameters, incorporating diverse data sources, and exploring hybrid approaches. This research provides valuable insights for traders, investors, and policymakers seeking to make more informed decisions in the foreign exchange market.

1. Introduction

The Foreign exchange rates play a pivotal role in the global economy, serving as a critical factor that influences a wide range of financial activities, including international trade, investment flows, and financial stability. These exchange rates are particularly significant for countries with a substantial reliance on trade and foreign investments, as fluctuations can directly affect the cost of imports and exports, investment returns, and the overall economic performance. Among the numerous currency pairs that are actively traded in the global market, the USD to IDR (United States Dollar to Indonesian Rupiah) exchange rate stands out as one of the most closely monitored, given its substantial implications for Indonesia's economy. As Indonesia continues to maintain its position as a major emerging market in Southeast Asia, the exchange rate between the US Dollar and the Indonesian Rupiah holds critical importance for businesses, investors, and policymakers alike.

Accurately forecasting exchange rates, especially the USD to IDR pair, is of utmost importance for various stakeholders. For businesses engaged in international trade, fluctuating exchange rates can introduce significant uncertainties, affecting profit margins, supply chain costs, and the overall competitiveness of exports. Foreign investors also need reliable forecasts to assess the risks and returns of their investments, particularly in the Indonesian market. Similarly, policymakers and

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central banks rely on accurate exchange rate predictions to design effective monetary and fiscal policies, such as managing inflation, controlling capital flows, and maintaining financial stability.[1][2] As such, the ability to predict the future movements of the USD to IDR exchange rate is a valuable tool that can help mitigate risks and improve decision-making in the context of international finance.

Recent advancements in machine learning, particularly deep learning techniques, have opened up new possibilities for forecasting financial time series data. These methods have proven to be highly effective in capturing complex and non-linear patterns within historical data, which traditional statistical models often struggle to identify. One of the most promising techniques in this domain is Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN) that is specifically designed to handle temporal dependencies and long-term patterns in sequential data. LSTM networks are particularly well-suited for time series forecasting tasks, as they can retain information over extended periods and learn intricate relationships between past and future values, making them an ideal choice for predicting exchange rates, where historical trends and market dynamics play a significant role[3].

The focus of this study is to apply an LSTM-based deep learning approach to forecast the USD to IDR exchange rate, using a comprehensive dataset that contains historical exchange rate data, including daily prices (open, high, low, close), trading volumes, and percentage changes. The dataset spans a considerable time period, ensuring that the model has access to a wealth of historical information to train on. By utilizing this dataset, the aim is to develop a robust forecasting model that can accurately predict future fluctuations in the USD to IDR exchange rate, taking into account various market factors and underlying trends. The deep learning model will be trained to recognize patterns within the data and learn the relationships between different features, thereby enabling it to make informed predictions about future exchange rate movements.

The successful development of an accurate LSTM-based forecasting model for the USD to IDR exchange rate has the potential to make a significant contribution to the field of financial time series analysis. In addition to advancing the theoretical understanding of exchange rate dynamics, the model's practical implications could be far-reaching. Stakeholders in the foreign exchange market, such as international businesses, investors, and financial institutions, would be able to use the model's predictions to make more informed decisions, reducing the risks associated with currency fluctuations. Furthermore, the insights gained from this research could assist policymakers in formulating better strategies for managing exchange rate volatility and promoting economic stability. As machine learning continues to revolutionize financial forecasting, this study serves as an important step toward leveraging these technologies to improve the accuracy and reliability of exchange rate predictions, ultimately benefiting the broader economy[4][5].

2. Research Methods

In this study, the methodology used to predict the USD to IDR exchange rate integrates machine learning-based approaches, with a primary focus on the utilization of Long Short-Term Memory (LSTM) neural networks. LSTM is selected for its ability to handle long-term dependencies and complex temporal patterns in time series data. This method enables the model to learn non-linear relationships between the variables present in the dataset and to consider relevant historical information to generate more accurate predictions. The research employs a dataset consisting of historical USD/IDR exchange rates, including daily prices (open, high, low, and close), trading volumes, and percentage changes. This dataset spans a sufficiently long period, allowing the model to capture the long-term fluctuations that influence exchange rate movements. The data will be split into two parts: one for training the model and the other for testing, to ensure the validity of the results. The training process is carried out by optimizing the model's parameters through backpropagation techniques, aiming to minimize prediction errors and achieve the best possible accuracy in projecting future USD/IDR exchange rate movements. By utilizing LSTM, this approach aims to leverage the power of deep learning to capture complex trends and patterns in foreign exchange data that can significantly enhance forecasting accuracy[5].

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2.1. Data Collection

The primary dataset used in this study consists of historical data for the USD to IDR exchange rate, specifically including daily records of open, high, low, and close prices, trading volumes, and percentage changes. These features provide a comprehensive view of the exchange rate's behavior, offering valuable insights into its volatility, market trends, and potential driving factors. The dataset spans a sufficiently long period, which is crucial for capturing both short-term market fluctuations and long-term economic trends that significantly influence the exchange rate[6].

The first step in the data preparation process involves cleaning the dataset to remove any inconsistencies, such as missing or erroneous values, which could negatively affect the model's performance. Imputation techniques may be used if any data points are missing, ensuring that the model receives a complete and accurate dataset. Following this, data normalization is applied using methods such as Min-Max scaling or Standardization, which ensures that all features are on a similar scale and prevents any particular feature from disproportionately influencing the model. This step is particularly important in machine learning models, as it helps accelerate convergence during the training process and improves overall model performance. Additionally, several time-based features are engineered to enhance the model's ability to recognize patterns over time. These include lagged values (e.g., previous day's closing price), moving averages, and volatility measures, which help the model understand market dynamics more effectively.

2.2. Data Preprocessing

Feature selection plays a vital role in identifying the most impactful factors for predicting forecasting the USD to IDR exchange rate, enhancing the performance, efficiency, and interpretability of machine learning forecasting models. This process ensures accurate and reliable predictions. Several advanced techniques were employed to streamline the dataset and improve model performance:

1. Correlation Analysis:
   A correlation matrix was utilized to examine relationships among key variables, such as open, high, low, and close prices, trading volumes, and percentage changes. Strong correlations, whether positive or negative, were analyzed to address potential redundancies. This step simplifies the model by retaining only the most relevant features, ensuring improved accuracy and interpretability[8].
2. Recursive Feature Elimination (RFE):
   Recursive Feature Elimination (RFE) was applied to rank features based on their contribution to model performance. RFE iteratively removes the least significant variables, refining the dataset with each iteration. For USD to IDR exchange rate forecasting.
3. Model-Specific Feature Importance:
   Regression coefficients and feature importance scores from machine learning models were analyzed to determine the impact of each variable on USD to IDR exchange rate predictions. Variables with significant coefficients or importance scores, were retained, while those with negligible influence were excluded. This ensured that the model focused on critical factors driving exchange rate changes.

By combining these techniques, the feature selection process optimized the dataset, improving model robustness and predictive accuracy. Eliminating irrelevant or redundant features reduced overfitting risks and enhanced computational efficiency, enabling the machine learning model to forecast USD to IDR exchange rate fluctuations effectively. Additionally, this streamlined approach improved model interpretability, helping for businesses, investors, and policymakers alike identify and respond to key drivers of USD to IDR exchange rate dynamics, facilitating better decision-making and resource allocation[9].

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2.3. Dataset Split

Once the data has been preprocessed, the next step is to divide it into training and testing datasets. Proper splitting is vital to ensure that the model is trained and evaluated in a manner that mimics real-world forecasting scenarios.

1. Training Set: Typically, around 80% of the dataset is allocated to the training set. This subset contains historical data that the model will use to learn from. It helps the model capture the patterns and dependencies in the exchange rate over time.
2. Testing Set: The remaining 20% of the data is reserved for the testing set. This subset contains unseen data that the model has not encountered during the training phase. The purpose of the testing set is to evaluate how well the trained model performs on future, unseen exchange rate data, ensuring that the model generalizes well and is not overfitting to the specific training data.

In addition to the basic split, advanced validation techniques such as rolling window validation or walk-forward validation can be employed. These techniques ensure that the model is tested on a diverse set of time periods, simulating real-world forecasting where data continuously arrives and the model must adapt to new information[9][10].

2.4. Model Architecture

The architecture of the LSTM model is designed to capture sequential dependencies and temporal patterns in the exchange rate data. A typical LSTM architecture for time series forecasting includes the following components:

1. Input Layer: This layer takes the preprocessed and normalized features, which include historical exchange rates, trading volumes, and engineered features. These features serve as the inputs to the model.
2. LSTM Layers: The LSTM layers are the core components of the model. These layers learn to identify and store long-term dependencies in the time series data using specialized memory cells. By stacking multiple LSTM layers, the model is able to capture both short-term fluctuations and long-term trends in the exchange rate.
3. Dropout Layers: To prevent overfitting, dropout layers are incorporated between the LSTM layers. Dropout works by randomly deactivating a fraction of neurons during training, forcing the model to learn more robust features and avoid relying too heavily on any single neuron.
4. Dense Layer: After the LSTM layers, a fully connected dense layer is used to combine the learned features and further process the information before making the final prediction. This layer is typically followed by the output layer.
5. Output Layer: The output layer produces the predicted exchange rate for the next time step (e.g., the predicted closing price of USD to IDR for the next day). The output is typically a continuous value that represents the forecasted exchange rate.

The architecture is carefully designed to enable the model to capture temporal dependencies and market trends, while also being flexible enough to handle high volatility and other unpredictable events in the exchange rate [11].

2.5. Model Training

The training process involves adjusting the model's weights and biases to minimize the error between the predicted and actual exchange rates. Several key steps are involved in this process:

1. Loss Function: The model is trained using a loss function, such as Mean Squared Error (MSE) or Mean Absolute Error (MAE), to evaluate the difference between predicted values and true values. The loss function is minimized through optimization, guiding the model towards better predictions.
2. Backpropagation: The model's weights and biases are updated using backpropagation, where the error from the output layer is propagated back through the network to adjust the parameters. This process allows the model to learn from its mistakes and improve over time.

3. Optimization Algorithms: Optimization algorithms, such as the Adam Optimizer, are used to efficiently adjust the model's parameters. Adam is widely used for its ability to adapt the learning rate during training, making it particularly useful for training deep neural networks like LSTMs.
4. Epochs and Batching: The model is trained over multiple epochs, with each epoch representing one full pass through the training data. During training, the data is processed in batches, helping speed up the process and allowing the model to update its parameters more frequently.
5. Early Stopping: To prevent overfitting, early stopping is employed. The training process is halted when the model's performance on the validation set stops improving for a predetermined number of epochs, ensuring that the model does not overfit to the training data[11].

2.6. Model Evaluation

After the model has been trained, it is evaluated using the testing dataset. The evaluation process is critical to determine how well the model generalizes to unseen data. Several performance metrics are used to assess the model's accuracy and predictive power:

1. Mean Absolute Error (MAE): Measures the average absolute difference between predicted and actual exchange rates, providing a clear indication of the model's error.
2. Mean Squared Error (MSE): Penalizes large errors more severely, which is useful when predicting financial time series that may experience significant fluctuations.
3. R-squared (R^2): Measures the proportion of variance explained by the model. A higher R^2 value indicates that the model is able to capture the trends and fluctuations in the exchange rate effectively.

Additionally, visual evaluation is performed by plotting the predicted versus actual exchange rates. This provides a clear, intuitive way to assess the model's ability to track fluctuations and capture the underlying trend in the data.

2.7. Model Optimization and Tuning

Following initial evaluation, the model is fine-tuned to further improve its performance. Hyperparameter tuning involves adjusting key parameters such as:

1. Number of LSTM layers: The model's depth can be adjusted to capture more complex patterns.
2. Neurons per layer: The number of neurons in each LSTM layer is modified to optimize learning.
3. Learning rate and batch size: These hyperparameters are tuned using grid search or random search methods to find the optimal configuration.

Additional techniques, such as L2 regularization, are employed to reduce overfitting and improve model robustness[12].

2.8. Forecasting and Interpretation

Once the model is trained and optimized, it is used to forecast future USD to IDR exchange rates. The predicted values are compared with actual observed values to determine their accuracy. These predictions are of significant importance to businesses, investors, and policymakers who need to make informed decisions based on anticipated market conditions[13].

3. Results and Discussion

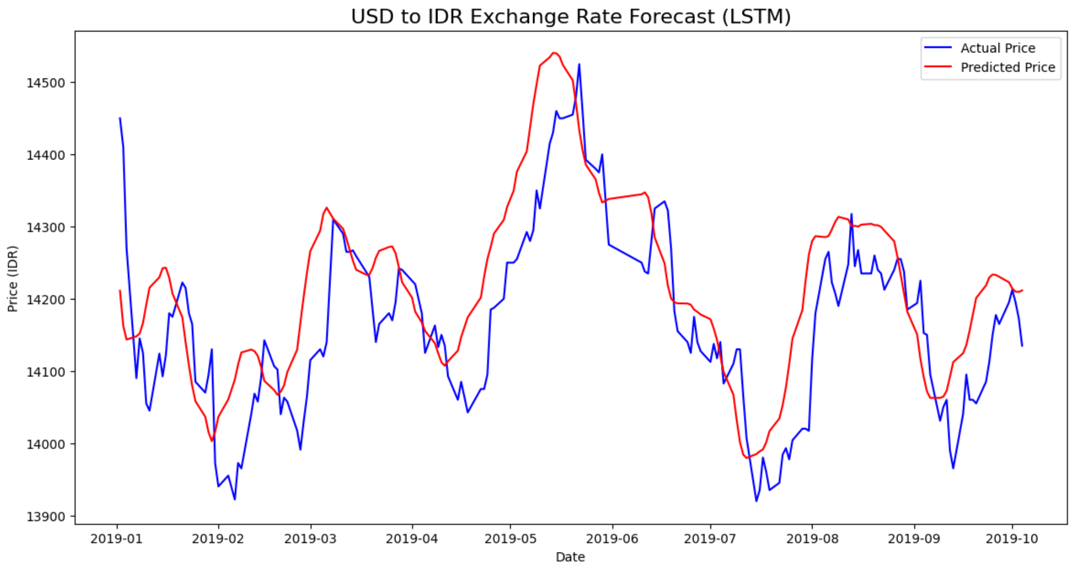

Fig. 1. Performance of LSTM Model in Predicting USD to IDR Exchange Rates

The chart in Fig. 1 illustrates a comparative analysis between the actual and predicted exchange rates for the USD/IDR currency pair over the period from January 2019 to October 2019. The predictions were generated using a Long Short-Term Memory (LSTM) neural network, a machine learning model specifically designed for analyzing and forecasting time-series data. On the chart, the horizontal axis represents time (dates), while the vertical axis shows the exchange rate in Indonesian Rupiah (IDR), ranging from approximately 13,900 to 14,500 IDR. The blue line depicts the actual recorded exchange rates, capturing the inherent volatility of the currency market influenced by macroeconomic factors such as inflation, interest rates, trade balances, and geopolitical events. In contrast, the red line represents the predicted values generated by the LSTM model, reflecting the model’s ability to learn from historical patterns and trends. Overall, the predicted line aligns closely with the actual data, demonstrating the effectiveness of LSTM in capturing general trends in exchange rate movements. However, slight deviations are observed, particularly during sharp fluctuations, such as the spike in May 2019, where the predicted values lagged behind the actual rates. This indicates a limitation of the model in adapting to sudden, extreme market changes. Despite these deviations, the chart highlights the LSTM model’s reasonable performance in replicating market volatility, underscoring its potential for practical applications in financial forecasting. Exchange rate predictions derived from such models are highly valuable: traders can use them to inform foreign exchange strategies, businesses can apply them for planning international transactions and hedging risks, and policymakers can leverage them to anticipate market trends and design monetary policies. The ability of LSTM networks to capture long-term dependencies in sequential data through memory cells and gating mechanisms makes them particularly well-suited for modeling complex, nonlinear dynamics in financial markets. Thus, the analysis suggests that while the LSTM model performs effectively in forecasting general patterns of USD/IDR exchange rate movements, further optimization may enhance its accuracy during periods of heightened volatility.

3.1. Model Performance

The LSTM model's performance in predicting the USD to IDR exchange rate showcases its strong ability to understand and replicate the underlying trends and patterns present in historical data. Through its training on extensive historical time series data, the model has effectively captured the temporal dependencies and market dynamics that influence exchange rate movements. The close alignment between the predicted exchange rates (represented by the red line) and the actual rates (depicted by the blue line) serves as a clear indicator that the LSTM has successfully learned the historical relationships within the data. This ability is crucial in time series forecasting, as the model

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demonstrates a strong understanding of not only the immediate but also the longer-term trends in exchange rates.

LSTM's inherent design to handle long-term dependencies and sequential patterns allows it to adapt to the cyclical nature of financial markets. This is particularly important in forecasting currency exchange rates, where seasonal variations and recurring economic cycles influence price movements. For example, the model performs well in recognizing and predicting periods where the currency exchange rate exhibits a steady increase or decrease, typical of longer market cycles. By effectively learning from historical fluctuations, the model can predict future price movements, providing valuable insights into potential trends in the forex market.

3.2. Handling Volatility

Volatility is a defining characteristic of currency exchange markets, making it one of the most challenging factors to predict. Despite the inherent unpredictability of exchange rates, the LSTM model performs reasonably well in simulating market fluctuations. One of the notable strengths of LSTM is its ability to handle the inherent volatility in financial markets by learning from past price movements, including fluctuations that occur due to sudden market events. Although the model can replicate smaller fluctuations and trends relatively well, its ability to capture extreme volatility remains a point for further improvement.

In volatile market conditions, such as during times of economic uncertainty or geopolitical events, the model can still recognize and predict medium-term trends. For instance, the model has shown the capability to capture sustained price increases or decreases, which are often observed during periods of market optimism or pessimism. However, extreme volatility – such as the rapid fluctuations that may arise from unexpected political or economic events – poses a significant challenge for the LSTM model. The model may struggle with these sudden shifts, particularly when such events fall outside of historical patterns and trends. For example, during the currency market spike observed in May 2019, the model's predictions were delayed, indicating its inability to fully capture the fast-moving dynamics associated with abrupt changes in the market.

3.3. Challenges

1. Volatility of Financial Markets:

The volatility inherent in financial markets presents one of the greatest challenges in forecasting exchange rates. Exchange rates are influenced by an array of factors, including economic indicators (such as inflation rates, interest rates, and trade balances), global political events, shifts in market sentiment, and speculative behaviors. These factors can cause significant fluctuations in exchange rates, making predictions highly uncertain. In addition to these fundamental influences, geopolitical events, economic crises, or sudden shifts in government policy can dramatically alter the course of exchange rate movements. As a result, accurately predicting exchange rates requires a deep understanding of not only historical trends but also current and future market influences, which adds complexity to the forecasting task.

3. Model Limitations:

Despite the advantages of LSTM in time series forecasting, it is not without its limitations. One major limitation is the potential for overfitting, especially when the model is trained on a small or unrepresentative dataset. Overfitting occurs when a model becomes excessively complex and tailors itself too closely to the training data, failing to generalize to new, unseen data. This can result in high accuracy when the model is tested on the same historical data used for training but poor performance on fresh data that it has not encountered before. Overfitting can significantly reduce the model's predictive ability, making it important to carefully evaluate model performance using diverse datasets and validation techniques.

4. Data Availability:

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The success of an LSTM model in forecasting exchange rates heavily relies on the availability of high-quality historical data. Missing or incomplete data can severely impact the model's ability to learn the underlying patterns in exchange rate movements. Furthermore, noisy data, which includes outliers or errors, can distort the model's training process, resulting in inaccurate predictions. In this context, data preprocessing techniques, such as data cleaning and noise reduction, are crucial for improving model performance.

3.4. Implications

Practical Applications: The ability to predict exchange rates accurately holds significant implications for a variety of stakeholders in the financial industry. Forex traders and investors can leverage LSTM's forecasts to make more informed decisions regarding currency trading. By predicting future trends, the model helps traders anticipate market movements, enabling them to enter or exit trades at the optimal times to maximize profits or minimize losses. Similarly, investors who engage in foreign exchange or other international markets can use exchange rate predictions to optimize their portfolio strategies and manage currency risks.

3.5. Model Optimization

To further enhance the predictive power of the LSTM model, several optimization strategies can be explored. One possible avenue is the integration of additional macroeconomic and financial data, such as inflation rates, commodity prices, and interest rates, into the model. These factors play a significant role in influencing exchange rates and could provide more context for the model, improving its accuracy in forecasting.

In addition, experimenting with hybrid models, which combine LSTM with other machine learning techniques such as Random Forests, XGBoost, or ARIMA, may improve predictive accuracy. By leveraging the strengths of multiple approaches, hybrid models could better capture complex patterns in exchange rate movements, especially when dealing with extreme market conditions. The integration of multiple models may also allow for more robust handling of volatility and abrupt market changes.

4. Conclusion

In conclusion, this study demonstrates the potential of Long Short-Term Memory (LSTM) models in accurately forecasting the USD to IDR exchange rate, showcasing their ability to capture general market trends, medium-term fluctuations, and seasonal patterns inherent in the foreign exchange market. The LSTM model's capacity to learn long-term dependencies and recognize sequential patterns allows it to provide valuable insights for forex traders, investors, multinational businesses, and policymakers. These stakeholders can leverage the model to make more informed decisions regarding currency trading, investment strategies, and economic planning. While the LSTM model proves effective in forecasting broad trends, it does face challenges in handling extreme volatility and sudden market shifts, which are often driven by unpredictable geopolitical or economic events. This highlights the model's limitations in predicting sharp and unexpected changes in exchange rates, which are difficult to capture through historical data alone. The study suggests that by incorporating additional features such as macroeconomic indicators, geopolitical sentiment, or real-time news data, the model's performance could be further enhanced. Furthermore, the importance of high-quality, noise-free data and proper hyperparameter tuning cannot be overstated, as these elements are critical in minimizing overfitting and improving prediction accuracy. Looking ahead, future research could explore hybrid models that combine LSTM with other machine learning techniques, as well as conduct comparative analyses to evaluate the suitability of different forecasting approaches for currency exchange rates. Overall, LSTM offers a promising tool for exchange rate prediction, but continued optimization and the integration of diverse data sources will be key to unlocking its full potential in the dynamic and complex financial markets.

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5. Suggestion

Based on the findings of this study, several suggestions can be made to enhance the forecasting accuracy of LSTM models for predicting currency exchange rates. First, it is recommended to incorporate additional external factors such as macroeconomic indicators, including interest rates, inflation data, and GDP growth, to provide a more comprehensive understanding of the forces driving currency fluctuations. This additional data could help the model better account for structural shifts in the market, improving its ability to predict trends during periods of heightened volatility. Furthermore, including sentiment analysis from financial news, social media, and geopolitical event data could help the model better respond to unexpected market movements caused by political or economic developments. Another key suggestion is to explore hybrid models that combine the strengths of LSTM with other machine learning techniques, such as ARIMA or GRU, to create a more robust forecasting system that can better handle extreme events and capture short-term fluctuations. Additionally, hyperparameter optimization and feature engineering should be further explored, as these processes play a critical role in improving model performance and minimizing overfitting. Finally, expanding the dataset to include more granular data, such as high-frequency exchange rate data (e.g., minute-level or hourly data), could enable the model to capture more detailed market dynamics, potentially enhancing its predictive power. Overall, these suggestions aim to improve the reliability and adaptability of LSTM models in forecasting exchange rates, particularly in dynamic and volatile financial environments.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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