Deep Learning for Exchange Rate Prediction Within Time Constrain

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Abstract: The implementation of an open economic system in Indonesia since 1969 has significant impact to the national economic growth. The high demand and supply of goods from within the country involved in international trade demonstrate a close correlation between export and import activities with the exchange rate of the rupiah. Economic stability is measured through the stability of the rupiah exchange rate against foreign currencies. The balance between demand and supply in the global market is considered crucial for creating a stable economy. History has recorded the Indonesian economic crisis in 1998, where the exchange rate of the rupiah against the US dollar drastically raises and causing challenges to the domestic production cost. This research aiming to make predictions using data science approach based on historical (time series) data. GRU, LSTM, and RNN algorithm being assess to perform the prediction. Results show that RNN algorithms generally outperform GRU and LSTM in making the prediction, particularly with limited time series data. Although RNN is typically superior, in one instance, GRU achieved slightly higher accuracy (0.047% difference) for the CNY to IDR pair over five years. Furthermore, the research highlights the substantial impact of batch size on algorithm accuracy, considering external factors such as interest rates. These findings offer valuable insights for economic decision-making and policy formulation.

Keywords: Exchange rate; GRU; LSTM; Prediction; RNN;

INTRODUCTION

The exchange rate (forex rate), represents the price of one unit of foreign currency in terms of domestic currency. The significance of exchange rates within an economic context lies in their role in fostering more open economic systems between nations. In the context of international trade, the different currencies during trading between each country becomes a relevant issue(Akhtar et al., 2022). Various factors influence the exchange rate of the Indonesian currency, including cross-border capital flows, such as interest rates, inflation rates, and the volume of imported goods (Biswas et al., 2023; Pahlevi et al., 2023a; Sri Mulyani et al., 2019).

Indonesia adopted an open economic system in 1969, and its economy has steadily progressed over the years (Amalutfia & Hafiyusholeh, 2020a; Verico & Pangestu, 2020). Economic instability in a country leads to increased production costs, resulting in higher prices of goods in the domestic market. In 1998, the exchange rate of the rupiah against foreign currencies weakened by 70%, reaching its peak in July 1998, with the rupiah reaching Rp 14,700 per US dollar (Amalutfia & Hafiyusholeh, 2020a; Pahlevi et al., 2023a; Verico & Pangestu, 2020).

Monitoring the fluctuations in the rupiah's exchange rate against the dollar is essential to ensure a country's economic stability. China emerged as a global economic powerhouse in 2019 and has maintained close economic ties with Indonesia (Budiastawa et al., 2019; Pahlevi et al., 2023a; Verico &

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Pangestu, 2020). Trade activities between Indonesia and China can cause fluctuations in the trade balance, which also impacts the exchange rate of the rupiah against the Chinese yuan. This research is conducted with the following considerations: serving as the basic framework and motivation for the author:

Economic stability is a primary concern for economic growth in Indonesia, with a focus on fluctuations in the exchange rate of the rupiah against foreign currencies. The research focuses on analyzing the impact of fluctuations in the exchange rate of the rupiah against the US dollar and the Chinese yuan on Indonesia's economic stability and identifying the factors causing fluctuations in the rupiah's exchange rate. The 1998 economic crisis serves as an example of the negative impact of significant exchange rate fluctuations (Verico & Pangestu, 2020).

The research results are expected to make a significant contribution to maintaining Indonesia's economic stability in the future. Research objectives is to develop a predictive model for the exchange rate of the rupiah against foreign currencies, namely the US dollar and the Chinese yuan. Identify minimum amount of data and factors contributing to fluctuations in the exchange rate of the rupiah against the US dollar and the Chinese yuan. This research is expected to contribute to the field of applied data science by analyzing Indonesia's economic data through the development of predictive models to analyze fluctuations in the rupiah's exchange rate against the US dollar and the Chinese yuan. Providing interactive data visualization to assist economic stakeholders (investors and the public) in better understanding the dynamics of the rupiah exchange rate with limited numbers of data.

LITERATURE REVIEW

Forecasting process for a time-series data, such as predicting forex rate or crypto currency, will having a challenge in generating appropriate prediction value. Numerous research has been performed with several algorithm, such as machine learning and deep learning algorithm to find the most accurate result and specific performance test (Akhtar et al., 2022; Dautel et al., 2020a; Islam et al., 2020; Pahlevi et al., 2023; Seabe et al., 2023; Sri Mulyani et al., 2019). The most common used algorithm for forex forecasting were shown in Fig. 1.
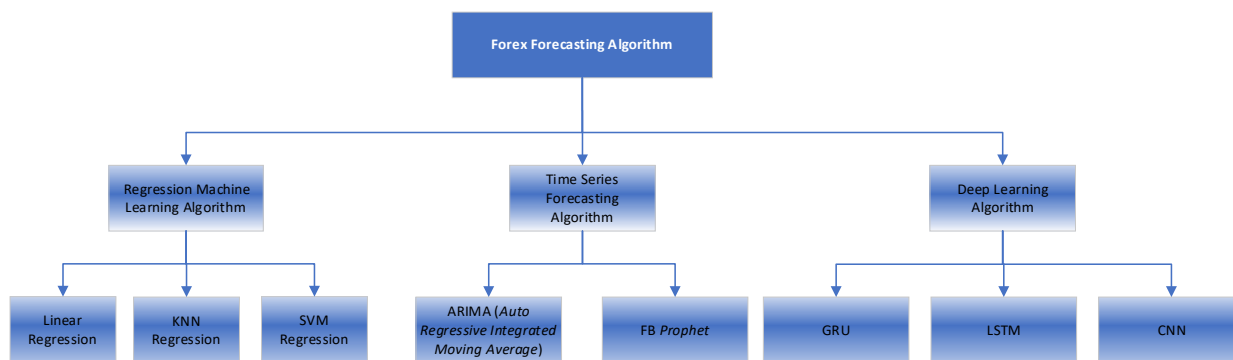

Fig. 1 Most Utilized Forex Forecasting Algorithm

In study conduct by Seabe (Seabe et al., 2023), for crypto forecasting with single data analysis, Bidirectional LSTM considered as the best algorithm for predicting the cryptocurrency prices, compared to GRU and LSTM. The performance models have been evaluated by considering the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE) with value of 0.036, which lower compare to GRU (0.041) and LSTM (0.124) result.

Study conducted by Dautel (Dautel et al., 2020a), for forex rate forecasting by evaluating traditional Recurrent Neural Network (RNN), Feedforward Neural Network (FNN), Gate Recurrent Unit (GRU) and Long Short-Term Memory (LSTM). The research concluded in general on forex forecasting, a simpler neural network may perform as well as if not better than a more complex deep neural network.

Panda (Panda et al., 2020) performed a subsequent Systematic Literature Review (SLR) focusing on the prediction of exchange rates employing Artificial Neural Networks (ANN) and Deep Learning Techniques. The study introduced innovative methodologies distinct from prior research spanning the

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timeframe from 2000 to 2019, with the objective of forecasting exchange rate patterns. The investigation presented the findings observed during the analyzed period utilizing latest updated proposed models such as Artificial Neural Network (ANN), an Auto-Regressive (AR), Functional Link Artificial Neural Network (FLANN), Hidden Markov Model (HMM), and Support Vector Regression (SVR) model. Several recently proposed neural network models for prediction have integrated theoretical principles and adopted a systematic methodology in model construction, thereby facilitating the advancement of innovative deep neural network architectures.

Pahlevi (Pahlevi et al., 2023a)conduct the research on forex prediction using LSTM and GRU algorithm. It use only use the USD to Euro exchange price to perform the analysis and considering the RMSE and MAE measures the predicting performance. The research demonstrates that the GRU model were more superior (MAPE reaching 0.037 and RMSE 0.054) and accurate compare to the LSTM model.

Ryll (Ryll & Seidens, 2019) conducted an investigation into the efficacy of machine learning algorithms for financial market forecasting, systematically reviewing over 150 pertinent publications. They curated a tabular representation delineating experiments across seven fundamental factors derived from an exhaustive literature examination. The research offers a standardized syntax for elucidating machine-learning algorithms and performs rank analyses to compare their efficacy based on criteria extracted from the surveyed literature. Machine-learning algorithms exhibit superior performance relative to conventional stochastic methods in financial market prediction, with recurrent neural networks demonstrating supremacy over feed-forward neural networks and support vector machines. This underscores the presence of exploitable temporal relationships within financial time series data spanning various asset classes and geographical regions.

Islam (Rahman et al., 2020) conducted a Systematic Literature Review (SLR) with a focus on recent advancements in FOREX currency prediction employing machine-learning algorithms. Employing a keyword-based search strategy, they identified pertinent research articles published between 2017 and 2019. Utilizing a selection algorithm, they delineated the inclusion criteria for their review, scrutinizing 39 articles sourced from "Elsevier," "Springer," and "IEEE Xplore" that prognosticated future FOREX prices within the specified timeframe. Their findings highlight a growing fascination among academics with neural network models, pattern-oriented methodologies, and optimization techniques. Particularly noteworthy is the extensive exploration of deep learning algorithms like the Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM), which demonstrate considerable potential in time series forecasting.

Sezer (Sezer et al., 2020) conducted a comprehensive evaluation of deep learning (DL) methodologies in the context of financial time series forecasting applications. They categorized research papers based on their utilization of Convolutional Neural Networks (CNNs), Deep Belief Networks (DBNs), and Long-Short Term Memory (LSTM) architectures. Their findings underscore a burgeoning interest in deep learning within the financial forecasting domain, driven by the adoption of novel DL models. Additionally, they provided insights into potential challenges and opportunities in the field to inform future research endeavors.

Berradi (Berradi et al., 2020) proposed that disseminating recent research on deep learning methodologies applied to the financial market can facilitate informed decision-making for investors. They curated recent articles discussing deep learning techniques employed for forecasting various aspects of the financial market, including trends in the commodity prices, stock market, forex rates, and stock indices. Their primary objective was to identify prevalent models utilized in recent research for addressing prediction challenges using Recurrent Neural Networks (RNNs), evaluating their attributes and novelty. They conducted a comprehensive examination of all stages of the forecasting process, encompassing preprocessing techniques, input feature selection, deep learning methodologies, and evaluation metrics employed. Their findings suggest that hybrid models outperform conventional machine learning techniques, indicating a strong association between the integration of diverse approaches and improved prediction accuracy.

Amalutfia (Amalutfia & Hafiyusholeh, 2020) performed research on predicting forex IDR to Yuan, using combination of Fuzzy Time Series-Markov Chain algorithm. The models evaluated though consideration of MAPE values on forecasting the next 24 weeks data, could achieve 0.53%.

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Most of previous research were only using forex pricing to perform the forecasting. And considering the study performed by Pangestu (Verico & Pangestu, 2020) in the real economy sector, which shows interest rate of central bank giving impact to the forex rate, in this study, the central bank interest rate will be used on forecasting forex process, to ensure the result could be more accurate and realistic to the actual condition.

Recurrent Neural Network (RNN)

RNNs are crafted specifically for processing sequential data, incorporating feedback loops that transmit the output signal of a neuron as a loop back into the neuron itself. This mechanism ensures the retention of information from previous time steps, encapsulated as the hidden state h_t, which influences network predictions. Conceptually, RNNs can be visualized as a series of interconnected neural network copies, each passing information to its subsequent copy. Formally, an RNN incorporates the previous time step's hidden state h_{t-1} as an additional parameter(Ni et al., 2019).

The hidden state formula is given by

$$h_t = f(W_{hx}.x_t + W_{hh}.h_{(t-1)} + b_h) \quad (1)$$

The output state formula is given by

$$y_t = g(W_{hy}.h_t + b_y) \quad (2)$$

Here, "W_{hh}" represents the Weight matrix that defines the transformation from the previous hidden state "h_{t-1}" to the current hidden state "h_t". "b_h" represent the bias vector for the hidden layer, "f" represents the activation function applied to the hidden layer, "y_t" represent the output at time step "t". "W_{hy}" representing Weight matrix that defines the transformation from the hidden state "h_t" to the output "y_t", "b_y" is the output layer bias vector, and "g" is the activation function applied to the output layer.

The primary objective of training a neural network is to minimize the loss function, which represents the collective disparity between the model's outputs and the actual labels. Given that a neural network's output is determined by the weights and biases of its connections, adjusting these parameters can alter the value of the loss function. Consequently, computing the gradient of the loss function with respect to the network's weights provides crucial information for training. The backpropagation algorithm leverages the insight that each weight's gradient can be computed by tracing back from the output gradient through the network, utilizing the chain rule.

In the context of RNNs, the process of training the network via gradient descent is termed "backpropagation through time," reflecting how error derivatives are not only propagated backward through the network itself but also through previous time steps via the recurrent connections (Dautel et al., 2020a).

In RNNs, activation functions like tanh or sigmoid have derivatives in the range of 0 to 1. This means that gradients of weights feeding into these functions get smaller as we compute successive derivatives using the chain rule. As a result, weights farther from the output layer have even smaller gradients. This issue, known as the gradient vanishing problem, which is amplified by the sequential data processing of the network. Essentially, the gradient signal diminishes not only across layers but also across time steps(Dautel et al., 2020b; Efriyani & Panjaitan, 2021). Consequently, RNNs struggle to capture long-term dependencies, prompting extensive research to address this challenge.

Long Short-Term Memory (LSTM)

The LSTM model, an abbreviation for Long Short-Term Memory, represents an advanced architecture stemming from the Recurrent Neural Network (RNN) framework and is classified within the realm of deep learning algorithms. Renowned for its adeptness in managing extensive sequences of data, the LSTM model exhibits proficiency in retaining information from preceding data points and leveraging it for forthcoming inputs. The fundamental configuration of an LSTM cell encompasses three distinct gates: the input gate, the forget gate, and the output gate, each of which incorporates sigmoid

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activation functions. Mathematically, the operations performed by all gates within the LSTM architecture are delineated by Equations (2)-(4).

The input gate formula (new information within the cell state) is given by:

$$j_{hb} = \sigma(X_{jq}[\, i_{(t-1)}, Yd] + cj) \quad (3)$$

The forget gate formula (invalid information to be discarded) is given by:

$$g_{hb} = \sigma(X_{gh}[\, i_{(t-1)}, Yd] + cg) \quad (4)$$

The output gate formula (activation of the last block for the final output) is given by:

$$m_{rh} = \sigma(X_{pq}[\, i_{(t-1)}, Yd] + cp) \quad (5)$$

Here, "σ" represents the sigmoid function, "Xy" denotes the neuron gate (x) weight, "$i_{(t-1)}$" represents the output from the previous LSTM block, "Yt" is the input value, and "cy" is the bias value.

In the structure of LSTM, with the top lines indicating memory in each cell which could be utilized to interconnect the transportation lines with the aid of the model, which could be used to manage data from previous memory to the current memory. Each LSTM node typically has a series of cells used for storing data flow (Pramod & Pm, 2021). To ensure that the recursive network has sufficient time for training and allows for the generation of long-distance cause-and-effect links, LSTM maintains errors at a more constant rate. In certain scenarios, neural networks and deep neural networks have exhibited enhanced forecasting efficacy in contrast to alternative machine learning models. Nonetheless, concerning the prediction of financial adversities, logistic regression models have showcased superior outcomes relative to neural network methodologies (Primananda & Isa, 2021).

Gated Recurrent Neural Network (GRU)

The GRU (Gated Recurrent Unit) represents an algorithmic model derived from the Recurrent Neural Network (RNN) framework, exhibiting distinctions that render it comparable to LSTM (Long Short-Term Memory). Notably, this model demonstrates superior computational efficiency and quicker training capabilities in contrast to LSTM, while concurrently facilitating the capture of prolonged dependencies within sequential data. The GRU architecture employs gating mechanisms to regulate the exchange of information between current and prior time steps. However, it is noteworthy that GRU incorporates solely two gates, specifically the reset gate and the update gate, in contrast to LSTM, which integrates three gating components.

The formula for the update gate is given by:

$$Y[t] = \sigma(V^y . W_t + T^y . g_{(t-1)}) \quad (6)$$

The formula for the reset gate is given by:

$$p[t] = \sigma(V^r . U_t + T^y . h_{(t-1)})) \quad (7)$$

Here, "Y[t]" represents the value of the update gate, "p[t]" is the value of the reset gate, "σ" denotes the sigmoid function, "V^y" represents the neuron gate, "U_t" represents the update gate, "$h_{(t-1)}$" is the output from the GRU block, "$g_{[t]}$" is the value of the hidden gate, and "W_t" is the input value.

In the context of forex data analysis, the Gated Recurrent Unit (GRU) operates by receiving a sequence of historical forex prices as input and subsequently generates a sequence of predicted stock prices as output. The input sequence undergoes processing within the GRU network, wherein the network's internal state is iteratively updated at each time step. Ultimately, the final state of the network

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is utilized to generate the desired output sequence (Rahman et al., 2020). Both LSTM and GRU algorithmic models possess distinct advantages attributable to their capacity to mitigate gradient-related challenges and seamlessly integrate with deep ensemble algorithms (Li & Pan, 2022).

METHOD

In this research, a systematic literature review was being used as a research approach since it is a defined and methodical way of discovering, evaluating, and studying existing material in order to analyze a certain research issue (Adams & Lawrence, 2019), as shown in Fig. 2.
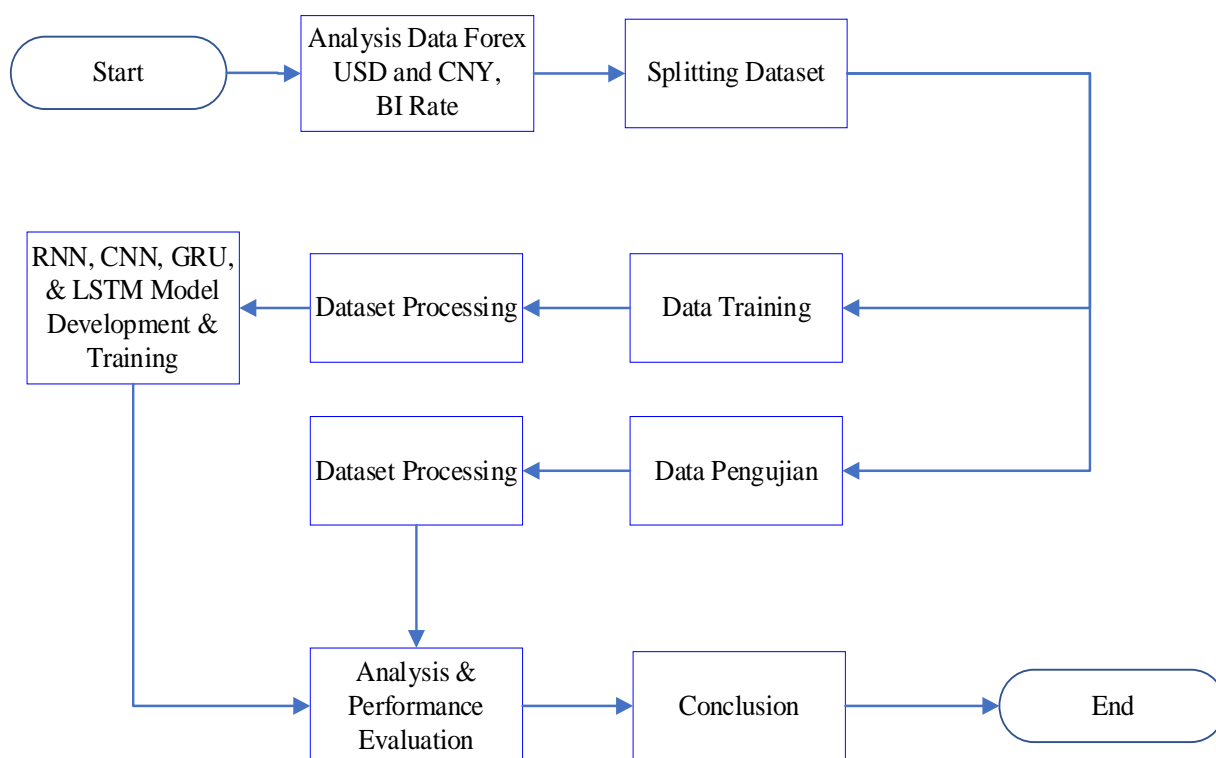

Fig. 2 Research Flow Chart

Dataset Description

In this research, primary data sourced from the global financial market news website, datainvesting.com, was utilized for forex rates, while data from bi.go.id was used for interest rate data. The dataset for USD to IDR spans from January 1997 to February 2024, comprising a total of 7007 data points, while the dataset for CNY to IDR spans from January 2000 to February 2024, totaling 6280 data points. Both forex and interest rate data are of numeric type (real type), with the forex data representing the average price for the respective currency pair on each day. The data employed in this study is retrospective, as it generates a temporal gap between the data used and the prediction outcomes. The collected data undergoes processing into multiple timeframes for testing purposes and is segmented into various data timelines to maximize predictive value.

Preprocessing

This study conducts preprocessing using Python, where data is inspected and dataset information is computed. Hardware libraries will be incorporated into this model due to their robust modularity and flexibility, which simplifies the construction of intricate RNN, LSTM, and GRU architectures through the integration of various layers and activation functions. These hardware libraries encompass features like regularization, dropouts, initializers, optimizers, and others.

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Dataset Allocation

In this study, two test scenarios are run by automatically splitting the dataset into two parts (training and testing) and applying various percentages to each component. Ratio for the training and testing data is 80%:20%. The prediction procedure involves retrieving the output of each model by importing the model file. Predicted values are obtained from the output of each model using the designated test and validation data. Additionally, a denormalization technique was used on the test data to assess and evaluate the model's performance outcomes.

Model Selection

This study makes currency forecasts using RNN, LSTM and GRU models.

Computer Hardware

To minimize possible interferences in the tests, all experiments were performed in the same environment, using a single computer with the following hardware specification:

CPU: AMD Ryzen 5 Pro 4650u (6 Cores)

Memory: 32 GB RAM

GPU: AMD Radeon Vega 7nm D3(Integrated)

OS: Windows 11 Pro 23H2

ML Implementation: Keras and Tensorflow 2.4.2

Analysis Result

In the analysis outcome, an assessment of the used model is carried out to identify any discrepancies that occurred during the prediction phase. The evaluation of model error resulting from predictions made using quantitative data is referred to as accuracy percentage, discrete accuracy (DA), and Mean Square Error (MSE). MSE serves to gauge the extent of deviation of data points from linear regression lines or to ascertain the concentration of data around such lines (Seabe et al., 2023). This evaluation metric, MSE which could be calculated using equation 7, is indicative of the accuracy of measurement results, where a lower MSE value (closer to 0) signifies higher accuracy.

Mean Absolute Error (MAE) measures the average absolute percentage error, serving as a statistical metric for assessing the accuracy of forecasts in the prediction process. MAE is user-friendly and readily understandable by the general public, making it a preferred method for evaluating forecast accuracy. This approach offers insights into the alignment of forecast errors with actual circuit values, and could be calculated using equation 8.

$$MSE = \frac{\sum_{t=1}^{n}(B_t - R_t)^2}{n} \quad (7)$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |B_t - R_t| \quad (8)$$

$$Accuracy\ (\%) = \frac{\sum_{t=1}^{n} C_t}{\sum T_p} x100\% \quad (9)$$

$$Discrete\ Accuracy\ (DA) = \frac{1}{n} \sum_{i=1}^{n}(B_t - R_t) \quad (10)$$

where Bt" is the actual value, "Rt" is forecast, " "n" is the number of time steps, "Ct" is the total amount of correct prediction, "Tp" is total number of prediction

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RESULT

In this section, the researcher will explain the results of the research obtained. In the first step, GRU, LSTM and RNN algorithm tested to process the CNY to IDR forex data with variative data quantity, as shown in Table 1.

Table 1 Summary Result of Algorithm Performance in CNY to IDR Forex

| Duration	Data Qty	Algorithm Model	Accuracy (%)	MSE(%)	MAE	DA
1 Quarter	90	GRU	92.889	7.111	0.232	0.882
1 Quarter	90	LSTM	85.745	14.255	0.345	0.882
1 Quarter	90	RNN	98.690	1.310	0.091	0.882
1 Year	285	GRU	98.057	1.943	0.106	0.946
1 Year	285	LSTM	97.021	2.981	0.130	0.857
1 Year	285	RNN	99.882	0.119	0.026	0.964
3 Year	806	GRU	99.246	0.550	0.560	0.900
3 Year	806	LSTM	99.138	0.638	0.604	0.894
3 Year	806	RNN	99.292	0.506	0.054	0.907
5 Year	1329	GRU	99.809	0.204	0.035	0.958
5 Year	1329	LSTM	99.454	0.585	0.057	0.913
5 Year	1329	RNN	99.762	0.254	0.039	0.940
23 Year	6280	GRU	99.997	0.003	0.004	0.994
23 Year	6280	LSTM	99.993	0.007	0.007	0.994
23 Year	6280	RNN	99.997	0.003	0.004	0.995
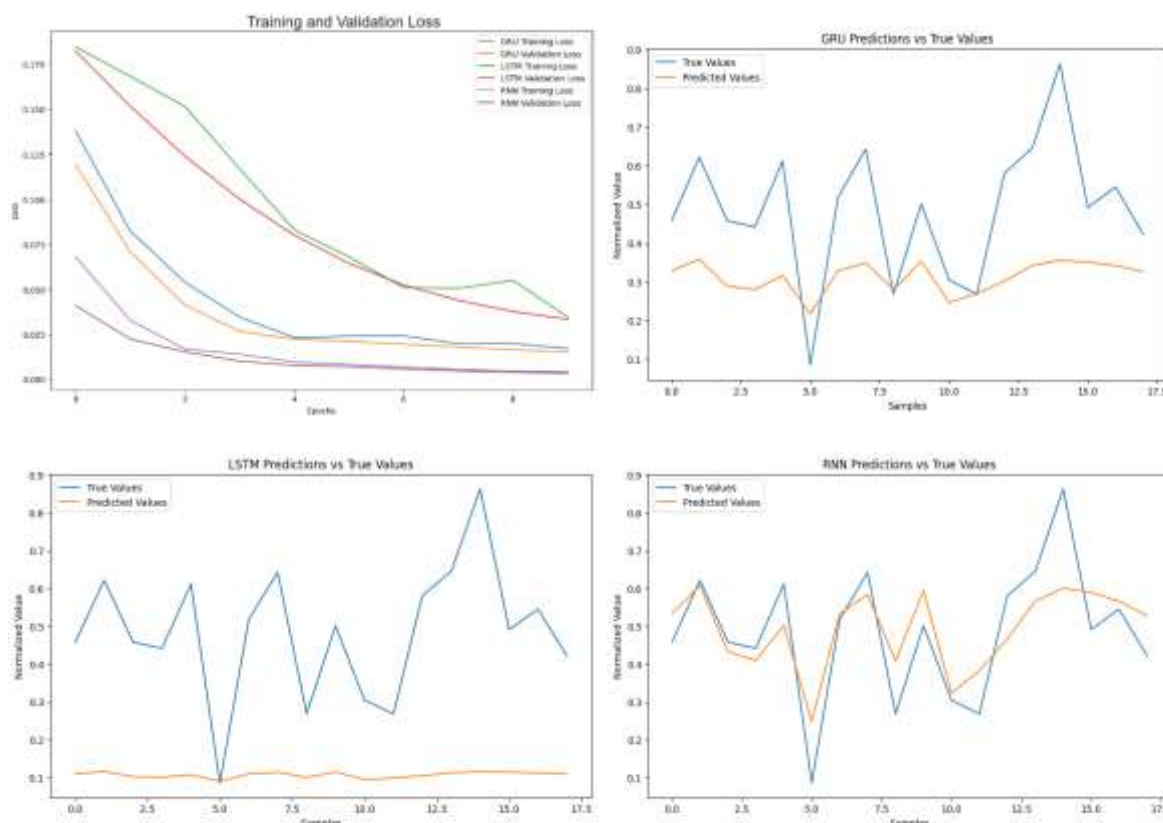
Fig. 3 Analysis of CNY to IDR with 1 Quarter data

Fig. 3 show the graphical result of GRU, RNN, LSTM and comparison of data validation loss using 1 Quarter forex data of CNY to IDR, with total 90 data. The result shows RNN has a highest accuracy with a very limited data source. LSTM has shown the lowest accuracy on this process, estimated the insufficient data quantity were causing this symptom occurred in LSTM.
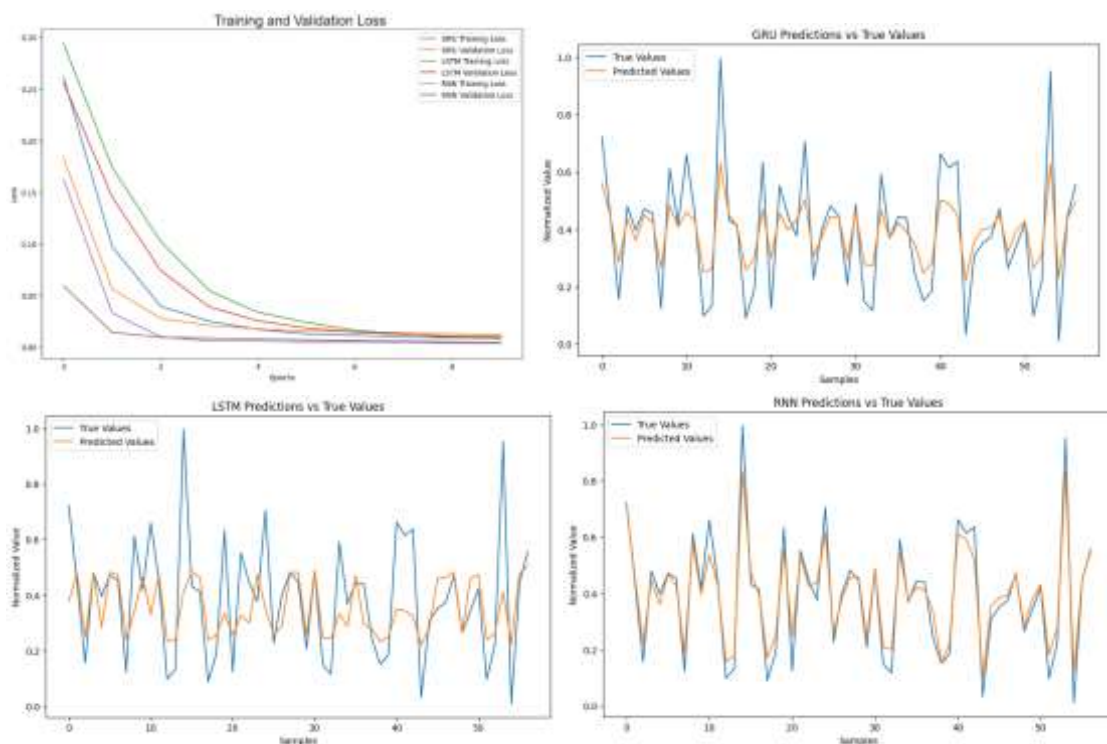
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Fig. 4 Analysis of CNY to IDR with 1 Years data

Fig. 4 show each algorithm performance when processing 1 year's forex data of CNY to IDR, with total 285 data. Overall, the forecasting accuracy were improved for each algorithm, once the data quantity increased. RNN algorithm shows as the highest accurate algorithm. Even though LSTM has shown as the lowest accuracy on this process, but the accuracy was improving significantly compare to previous process, when tested using 1 quarter data. The comparison graph of true value with prediction value, start to shows similarity.
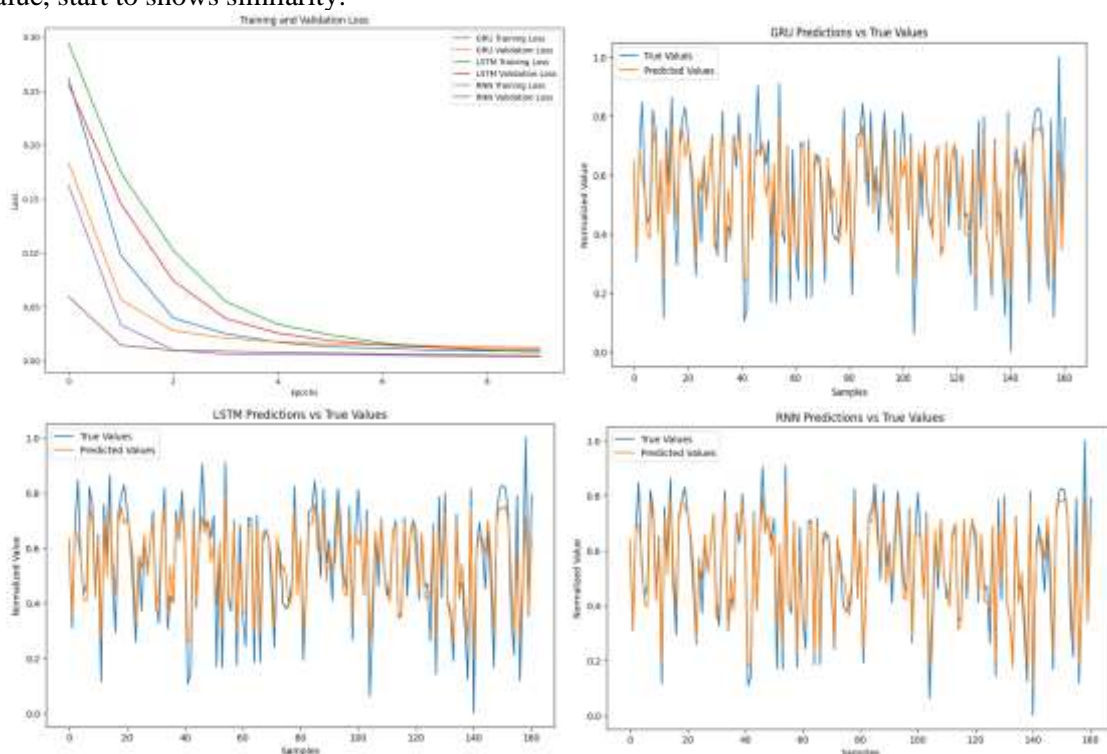

Fig. 5 Analysis of CNY to IDR with 3 Years data

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Fig. 5 show the RNN, LSTM, and GRU algorithm performance when processing 3 years forex data of CNY to IDR with total 806 data. RNN algorithm shows as the highest accuracy result. GRU shows the stable result on the second rank of accuracy result. Overall, the forecasting accuracy of each algorithm has a small gap and reaching more than 99%. The graph similarity results between prediction compare to true value during test for all algorithm, were align with the accuracy result were very high.

Fig. 6 shows the RNN, LSTM, and GRU algorithm performance when processing 5 year's forex data of CNY to IDR with total 1329 data. Once the data has more than 1000 data in the trial, GRU has shown a better accuracy performance among other algorithm in this research. Even though the gap between GRU and RNN in terms of accuracy, the MSE result shows LSTM has significant error result compare to another algorithm. The graph results between prediction compare to true value during test on all algorithm were have a very high similarity, which also show the high accuracy level on the forecasting process.
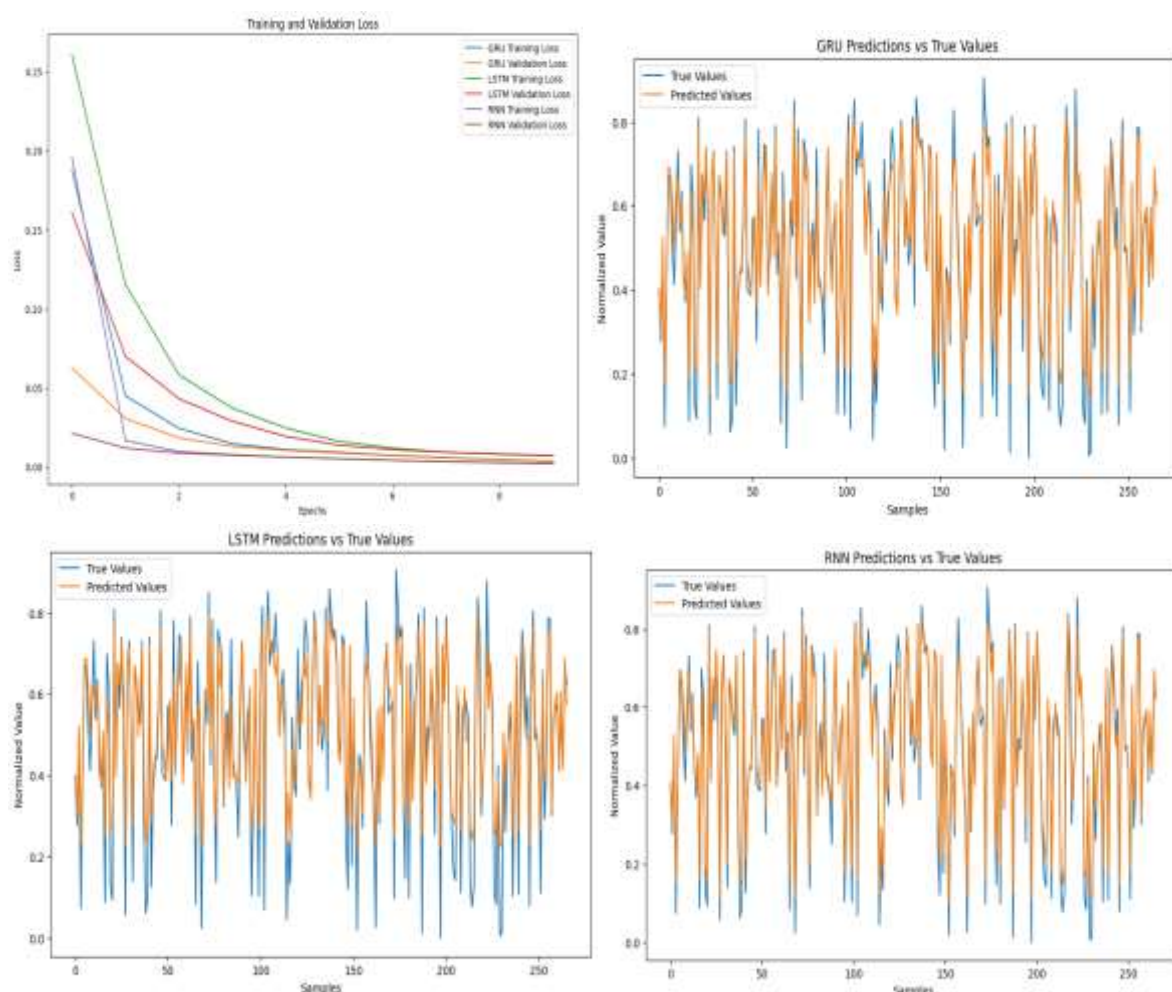

Fig. 6 Analysis of CNY to IDR with 5 Years data

Evaluating algorithm performance when processing 23 years forex data of CNY to IDR with total 6279 data, all algorithm shows similar accuracy performance, including the MSE result and MAE result, as seen in Table 1. To ensure the performance evaluation reliability, the LSTM, GRU, and RNN algorithm also tested to evaluate the USD to IDR forex data with variative amount of data. Table 2 shows the performance result on this second evaluation steps. The result shown a stable result which shows RNN were in the most accurate algorithm.

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Table 2 Summary Result of Algorithm Performance in USD to IDR Forex

Duration	Data Qty	Algorithm Model	Accuracy (%)	MSE(%)	MAE	DA
1 Quarter	90	GRU	92.245	7.754	0.221	0.823
1 Quarter	90	LSTM	86.708	13.291	0.287	0.823
1 Quarter	90	RNN	98.250	1.750	0.109	0.824
1 Year	285	GRU	99.108	0.879	0.076	0.962
1 Year	285	LSTM	97.689	2.257	0.116	0.962
1 Year	285	RNN	99.408	0.590	0.062	0.962
3 Year	806	GRU	99.427	0.570	0.061	0.960
3 Year	806	LSTM	99.971	1.024	0.083	0.948
3 Year	806	RNN	99.945	0.052	0.017	0.974
5 Year	1329	GRU	99.941	0.059	0.020	0.968
5 Year	1329	LSTM	99.863	0.137	0.032	0.972
5 Year	1329	RNN	99.967	0.032	0.012	0.976
27 Year	7007	GRU	99.990	0.010	0.005	0.987
27 Year	7007	LSTM	99.984	0.012	0.007	0.987
27 Year	7007	RNN	99.991	0.009	0.004	0.984

DISCUSSIONS

The data used in this research were classified as time series data. The performance evaluation during this research was performed by using the performance matrix shown in Table 1 and Table 2, which displaying the accuracy level, mean square error, mean absolute error, and discrete accuracy. The finding during this study shows overall the RNN algorithm in forecasting forex exchange rate to IDR, was showing the best performance compare to GRU and LSTM when handling time series data. Even though there is one time, RNN accuracy were beaten by GRU when handling 5 years data for "CNY to IDR", as shown in Table 3. It is also shown with very limited amount of data to process, RNN were more superior compare to GRU and LSTM on making the forecast, with error < 0.37%. this accuracy result was better compared to research done by(Amalutfia & Hafiyusholeh, 2020; Pahlevi et al., 2023).

Table 3 Summary Result of Algorithm Accuracy Comparison for Forex Forecasting

Algorithm Model	Forex Type	Accuracy (%) 1Q	Accuracy (%) 1 Year	Accuracy (%) 3 Years	Accuracy (%) 5 Years	Accuracy (%) ≥23 Years
GRU	CNY to IDR	92.889	98.057	99.246	99.809	99.997
LSTM	CNY to IDR	85.745	97.021	99.138	99.454	99.993
RNN	CNY to IDR	98.690	99.882	99.292	99.762	99.997
GRU	USD to IDR	92.245	99.108	99.427	99.941	99.990
LSTM	USD to IDR	86.708	97.689	99.971	99.863	99.984
RNN	USD to IDR	98.250	99.408	99.945	99.967	99.991

*name of corresponding author

The result above were using standard parameter of each algorithm. Further research could be done by modifying the algorithm parameter, such as number of neural network layers, activation functions, dropout regularization, learning rate, and sequence length (look back). However, adjusting those parameters is a process of trial and error, which may increase computational costs and training time. Combining the experiment with domain knowledge and understanding the dataset specific characteristic will be required to perform this step.

CONCLUSION

Base on the analysis and experiment conducted during this research, it can be concluded that the performance of RNN algorithms in forecasting forex exchange rates to IDR generally outperformed GRU and LSTM algorithms especially when handling time series data with very limited amount of data. However, it is noteworthy that in one instance, GRU achieved higher accuracy compared to RNN when handling a specific currency pair (CNY to IDR) over a five-year period with very small gap differences (0.047%). The research result also indicates that batch size affecting significantly the accuracy of the algorithm to forecasting the exchange rate which considering the interest rate as external factor.

REFERENCES

Adams, K. A., & Lawrence, E. K. (2019). *Research Methods, Statistics, and Applications* (2nd Editio). SAGE.

Akhtar, S., Ramzan, M., Shah, S., Ahmad, I., Khan, M. I., Ahmad, S., El-Affendi, M. A., & Qureshi, H. (2022). Forecasting Exchange Rate of Pakistan Using Time Series Analysis. *Mathematical Problems in Engineering*, *2022*, 1–11. https://doi.org/10.1155/2022/9108580

Amalutfia, S. Y., & Hafiyusholeh, Moh. (2020a). Analisis Peramalan Nilai Tukar Rupiah Terhadap Dollar dan Yuan Menggunakan FTS-Markov Chain. *VYGOTSKY*, *2*(2), 102. https://doi.org/10.30736/vj.v2i2.258

Amalutfia, S. Y., & Hafiyusholeh, Moh. (2020b). Analisis Peramalan Nilai Tukar Rupiah Terhadap Dollar dan Yuan Menggunakan FTS-Markov Chain. *VYGOTSKY*, *2*(2), 102. https://doi.org/10.30736/vj.v2i2.258

Berradi, Z., Lazaar, M., Mahboub, O., & Omara, H. (2020). A Comprehensive Review of Artificial Intelligence Techniques in Financial Market. *2020 6th IEEE Congress on Information Science and Technology (CiSt)*, 367–371. https://doi.org/10.1109/CiSt49399.2021.9357175

Biswas, A., Uday, I. A., Rahat, K. M., Akter, Mst. S., & Mahdy, M. R. C. (2023). Forecasting the United State Dollar(USD)/Bangladeshi Taka (BDT) exchange rate with deep learning models: Inclusion of macroeconomic factors influencing the currency exchange rates. *PLOS ONE*, *18*(2), e0279602. https://doi.org/10.1371/journal.pone.0279602

Budiastawa, I. D. G., Santiyasa, I. W., & Pramartha, C. R. adi. (2019). Prediksi Dan Akurasi Nilai Tukar Mata Uang Rupiah Terhadap US Dolar Menggunakan Radial Basis Function Neural Network. *Jurnal Elektronik Ilmu Komputer Udayana*, *7*(4), 309–317.

Dautel, A. J., Härdle, W. K., Lessmann, S., & Seow, H.-V. (2020a). Forex exchange rate forecasting using deep recurrent neural networks. *Digital Finance*, *2*(1–2), 69–96. https://doi.org/10.1007/s42521-020-00019-x

Dautel, A. J., Härdle, W. K., Lessmann, S., & Seow, H.-V. (2020b). Forex exchange rate forecasting using deep recurrent neural networks. *Digital Finance*, *2*(1–2), 69–96. https://doi.org/10.1007/s42521-020-00019-x

*name of corresponding author

Efriyani, D., & Panjaitan, F. (2021). Klasifikasi Malware Dengan Menggunakan Recurrent Neural Network. *Jurnal Ilmiah Matrik*, *23*(3), 310–316. https://doi.org/10.33557/jurnalmatrik.v23i3.1592

Islam, Md. S., Hossain, E., Rahman, A., Hossain, M. S., & Andersson, K. (2020). A Review on Recent Advancements in FOREX Currency Prediction. *Algorithms*, *13*(8), 186. https://doi.org/10.3390/a13080186

Li, Y., & Pan, Y. (2022). A novel ensemble deep learning model for stock prediction based on stock prices and news. *International Journal of Data Science and Analytics*, *13*(2), 139–149. https://doi.org/10.1007/s41060-021-00279-9

Ni, L., Li, Y., Wang, X., Zhang, J., Yu, J., & Qi, C. (2019). Forecasting of Forex Time Series Data Based on Deep Learning. *Procedia Computer Science*, *147*, 647–652. https://doi.org/10.1016/j.procs.2019.01.189

Pahlevi, M. R., Kusrini, K., & Hidayat, T. (2023a). Comparison of LSTM and GRU Models for Forex Prediction. *Sinkron*, *8*(4), 2254–2263. https://doi.org/10.33395/sinkron.v8i4.12709

Pahlevi, M. R., Kusrini, K., & Hidayat, T. (2023b). Comparison of LSTM and GRU Models for Forex Prediction. *Sinkron*, *8*(4), 2254–2263. https://doi.org/10.33395/sinkron.v8i4.12709

Panda, M. M., Panda, S. N., & Pattnaik, P. K. (2020). Exchange Rate Prediction using ANN and Deep Learning Methodologies: A Systematic Review. *2020 Indo – Taiwan 2nd International Conference on Computing, Analytics and Networks (Indo-Taiwan ICAN)*, 86–90. https://doi.org/10.1109/Indo-TaiwanICAN48429.2020.9181351

Pramod, & Pm, M. (2021). Stock Price Prediction Using LSTM. *Test Engineering and Management*, *83*, 5246–5251.

Primananda, S. B., & Isa, S. M. (2021). Forecasting Gold Price in Rupiah using Multivariate Analysis with LSTM and GRU Neural Networks. *Advances in Science, Technology and Engineering Systems Journal*, *6*(2), 245–253. https://doi.org/10.25046/aj060227

Rahman, M., Islam, D., Mukti, R. J., & Saha, I. (2020). A deep learning approach based on convolutional LSTM for detecting diabetes. *Computational Biology and Chemistry*, *88*, 107329. https://doi.org/10.1016/j.compbiolchem.2020.107329

Ryll, L., & Seidens, S. (2019). *Evaluating the Performance of Machine Learning Algorithms in Financial Market Forecasting: A Comprehensive Survey*.

Seabe, P. L., Moutsinga, C. R. B., & Pindza, E. (2023). Forecasting Cryptocurrency Prices Using LSTM, GRU, and Bi-Directional LSTM: A Deep Learning Approach. *Fractal and Fractional*, *7*(2), 203. https://doi.org/10.3390/fractalfract7020203

Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning : A systematic literature review: 2005–2019. *Applied Soft Computing*, *90*, 106181. https://doi.org/10.1016/j.asoc.2020.106181

Sri Mulyani, E. D., Bachtiar, A., Suci R, D., Rifki, D., Yogaswara, I., & Tyas, N. S. (2019). Prediksi Kurs Rupiah Terhadap Dollar Amerika Menggunakan Metode Trend Moment. *INOVTEK Polbeng - Seri Informatika*, *4*(2), 147. https://doi.org/10.35314/isi.v4i2.1029

Verico, K., & Pangestu, M. E. (2020). The Economic Impact of Globalisation in Indonesia. *ERIA Discussion Paper Series*, *338*, 1–30.

*name of corresponding author