
Foreign Exchange Prediction using LSTM Optimized with Genetic Algorithm

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Abstract

Foreign exchange (Forex) was one of the largest financial markets in the world, with more than \$5.1 trillion being traded every day. In this study, Long Short-Term Memory (LSTM) and Genetic Algorithm Long Short-Term Memory (GA-LSTM) were used to predict the price patterns of USD, EUR, and SGD. The data was taken from the Google Finance website over a period of 5 years, totaling about 1977 data points for USD and EUR, and 1956 data points for SGD. In some scenarios, optimization with Genetic Algorithms was successful in reducing error values, although this did not always apply to all cases. The most optimal LSTM model for predicting USD, EUR, and SGD data against IDR obtained an MAE of around 41.27, 60.89, and 13.04 respectively. However, if we were to predict future prices, the EUR model would need to be improved further to obtain a smaller error value.

Keywords: Foreign exchange, Long Short-Term Memory, Genetic Algorithm

1. Introduction

Foreign exchange (Forex) is one of the world's largest financial markets, with more than \$5.1 trillion traded every day. The intricacies and fluctuations inherent in Forex render price prediction challenging [1], particularly in regions like Indonesia where fostering sustainable economic development and enhancing citizens' welfare is paramount. Exchange rate instability poses a significant deterrent to investor confidence, potentially hindering Indonesia's developmental progress, given the substantial role foreign investors play in its economic growth [2]. The consequential impact of such instability cannot be overstated, especially considering the pivotal role that foreign investors have historically played in propelling Indonesia's economic growth trajectory forward. As such, mitigating the adverse effects of exchange rate fluctuations assumes paramount importance, necessitating robust predictive models and strategic interventions to navigate the complexities of the Forex landscape effectively.

The realm of Deep Learning, celebrated for its triumphs in diverse domains like image recognition, natural language processing, and speech recognition, has garnered considerable attention for its applicability in forecasting exchange rates [3, 4, 5]. This burgeoning interest is evident across the global financial landscape, where financial researchers have dedicated substantial efforts to studying and analyzing the intricacies of both stock and Forex markets. The advent of artificial intelligence has revolutionized investment strategies, precipitating a notable uptick in the utilization of Deep Learning models by investors seeking to predict and analyze stock and Forex prices. Over time, empirical evidence has firmly established the efficacy of Deep Learning methodologies in successfully predicting fluctuations in both stock and Forex prices [5]. This convergence of technological innovation and financial analysis underscores the evolving nature of investment practices and the increasing reliance on sophisticated computational tools to navigate the complexities of modern financial markets.

Based on one of the literature, it's evident that the Long Short-Term Memory (LSTM) model outshines its counterpart, the Recurrent Neural Network (RNN), exhibiting superior performance characterized by smaller Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics [6]. Building upon this foundation, we endeavor to harness the predictive prowess of the LSTM model to forecast foreign exchange prices over the past five years. By leveraging this advanced neural network architecture, we aim to enhance the accuracy and reliability of our predictions, thereby facilitating more informed decision-making in the volatile realm of foreign exchange markets. Furthermore, to further refine and optimize the LSTM

model, we propose the integration of Genetic Algorithms (GA). By iteratively fine-tuning the model parameters through GA, we anticipate a reduction in errors from the initial model, thus bolstering the predictive capabilities of our approach.

2. Research Method

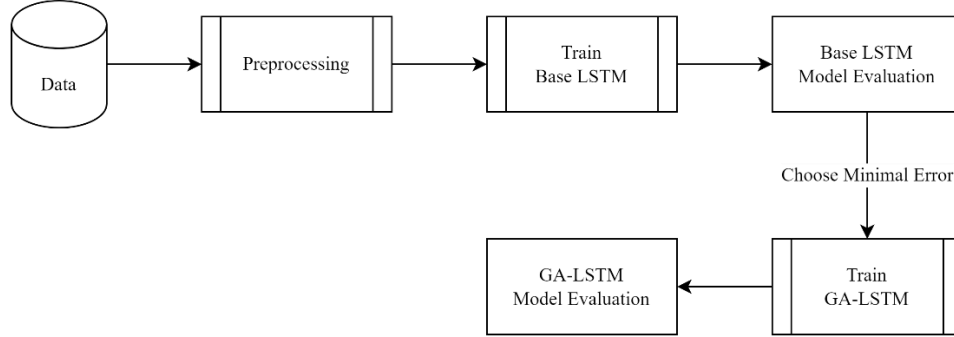


Figure 1. Research Procedure

The research procedure consists of the following steps (Fig. 1):

1. Data acquisition, data for this research acquired from Google Finance and consist of daily closing purchase prices for the USD, EUR, and SGD foreign currencies. The dataset covers a timeframe of about five years, from January 1, 2018, to May 31, 2023, encompassing a total of 1977 data points for the USD and EUR currencies, and 1956 data points for the SGD currency.
2. Data preprocessing, involves transforming the initially unrefined data into a clean format suitable for model training. This entails several steps such as identifying and handling outliers, normalizing the data, implementing sliding window techniques, and partitioning the dataset using either splitting or cross-validation techniques.
3. Train LSTM, Base LSTM has 3 layers with cell numbers of 128, 64, and 32 respectively. The model will be trained using various parameters including, number of layers, sliding window size, train-test split or fold size from cross-validation. Details of the model and tested parameters can be seen in Fig. 2 and Table 1.
4. LSTM evaluation, the model that has been trained will be tested using previously split data to get the error value. The matrix used to get it is MAE.
5. Train GA-LSTM, choose parameters from Base LSTM that produce a model with minimum MAE in each sliding window, where the number of cells in LSTM will then be optimized using GA. The number of generations used for GA is 50, where mutations will occur every generation in multiples of 5. After getting the optimal number of cells for each LSTM layer, the model will be retrained using the optimal results obtained through GA.
6. GA-LSTM evaluation, the retrained model will be tested using previously split data to get the MAE.

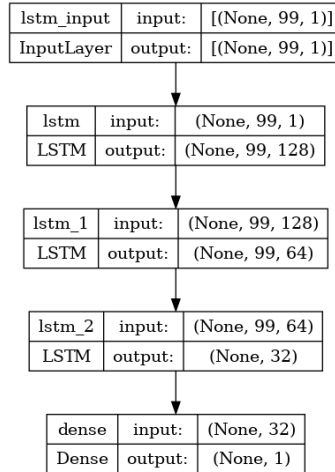


Figure 2. Base LSTM Architecture

Table 1. Tested Parameter

LSTM Layers	Sliding Window	Split or Fold
1	5	0.8 / 5
2	10	0.9 / 10
3	20	

3. Results and Analysis

Out of the comprehensive set of 36 tests conducted utilizing the Base LSTM model across different currency types, a total of 18 models emerged as candidates suitable for optimization through the application of GA-LSTM. This transition from the initial LSTM framework to the GA-LSTM variant signifies a deliberate effort to refine and enhance the predictive capabilities of the models.

To facilitate a thorough analysis, the author employs a diverse array of graphical representations, including bar charts, to visually encapsulate the findings and insights gleaned from the experimentation process.

3.1. USD/IDR Dataset

In both the Split and Cross Validation scenarios, the outcomes of optimizations utilizing GA-LSTM varied significantly. In the Split scenario, depicted in Figure 3, the majority of optimization attempts proved unsuccessful, with only one instance, namely scenario 14, demonstrating complete success where GA-LSTM yielded lower error values than Base LSTM. Conversely, in the Cross Validation scenario, illustrated in Figure 4, a majority of optimization endeavors using GA-LSTM were deemed successful, as evidenced by scenarios 2, 3, 9, 15, and 17. Despite variations in error values across different scenarios, some of the observed increases were generally not substantial.

However, even amidst these successes, scenario 15 stood out, as the optimal model emerged from the Base LSTM architecture with Split technique. Despite GA-LSTM presenting a slightly higher error value of 0.79 in this case, it did not yield the ultimate solution. This discrepancy underscores the complexity of model selection, emphasizing the need to consider factors beyond mere error metrics. While GA-LSTM showed potential in minimizing error, it fell short in providing the most suitable solution within this specific context. Figure 5 shows how the model performs in predicting USD currency prices.

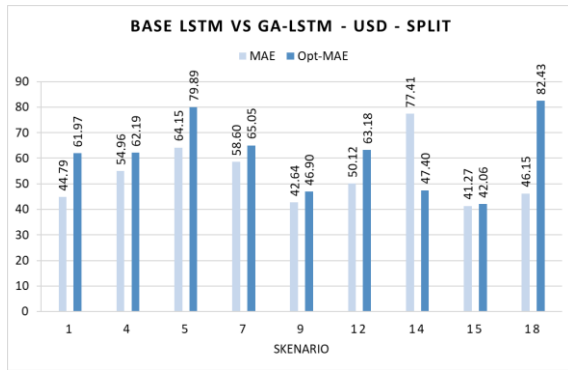


Figure 3. Comparison chart of Base LSTM vs GA-LSTM – USD – Split

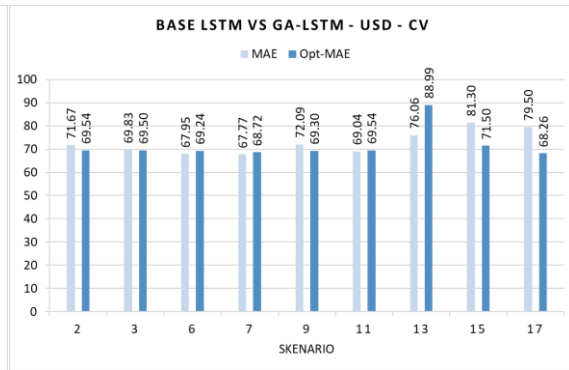


Figure 4. Comparison chart of Base LSTM vs GA-LSTM – USD – CV

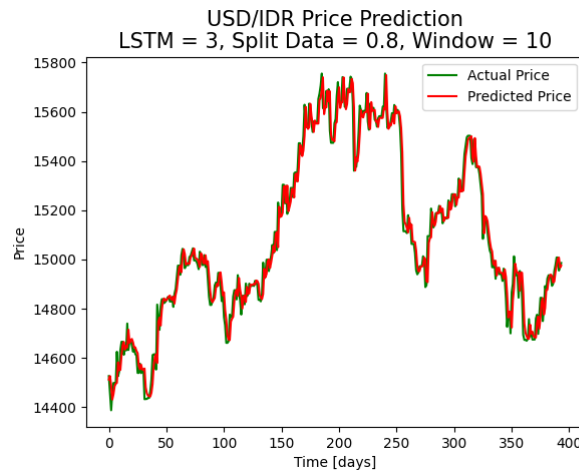


Figure 5. USD Optimal Model Price Prediction

3.2. EUR/IDR Dataset

The analyses of both the split and cross-validation techniques reveal a predominant trend of successful optimizations with GA-LSTM across various scenarios. Specifically, in scenarios 8, 10, 12, 14, and 16 for the split technique, and in scenarios 5, 7, 13, and 15 for cross-validation, GA-LSTM consistently outperformed the Base LSTM model, yielding lower error values. While some scenarios exhibited slightly higher error values post-optimization, the overall increase was not substantial. These findings underscore the effectiveness of GA-LSTM in refining model performance and highlight its potential to enhance predictive accuracy in both split and cross-validation methodologies.

In scenario 10, split technique GA-LSTM emerged as the optimal model, highlighting its ability to handle intricate data patterns effectively. By combining genetic algorithms with LSTM architecture, the model demonstrated remarkable adaptability and evolution, leading to superior performance. Notably, the optimized model in scenario 10 achieved an impressive reduction in MAE by 3.98 units compared to the initial model. These findings underscore the effectiveness of GA-LSTM in refining predictive accuracy and emphasize its potential to revolutionize forecasting accuracy across various fields of application.

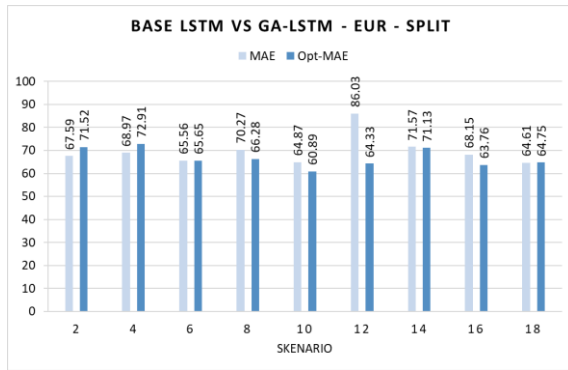


Figure 6. Comparison chart of Base LSTM vs GA-LSTM – EUR – Split

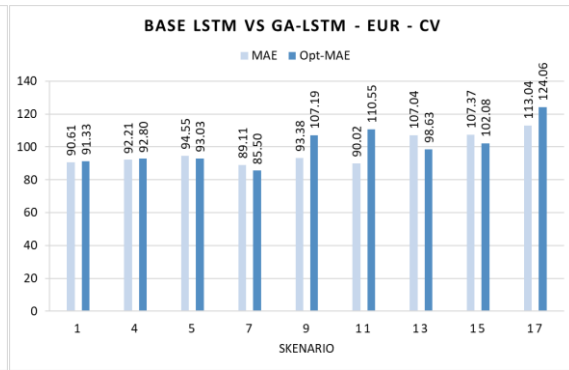


Figure 7. Comparison chart of Base LSTM vs GA-LSTM – EUR – CV

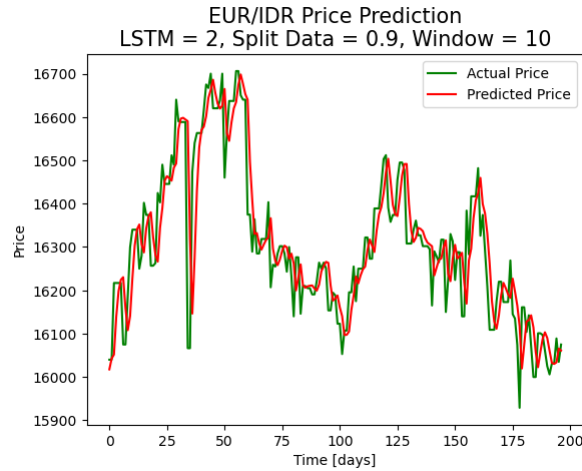


Figure 8. EUR Optimal Model Price Prediction

3.3. SGD/IDR Dataset

In both the split and cross-validation scenarios, the outcomes of optimizations using GA-LSTM predominantly veered towards being unsuccessful. However, a few instances stood out as successful, namely in split scenarios 2, 10, and 18, and in cross-validation scenarios 15 and 17. In these cases, the results obtained from GA-LSTM showcased lower error values compared to Base LSTM, indicating an improvement in predictive accuracy. Nonetheless, the majority of optimization attempts using GA-LSTM failed to outperform the Base LSTM models, as evidenced by higher error values. Additionally, while some scenarios exhibited slight increases in error compared to Base LSTM, the differences were marginal, as observed in cross-validation scenario 4.

Notably, in scenario 6, despite efforts to leverage GA-LSTM optimization techniques, the Base LSTM architecture emerged as the optimal model, with a considerable disparity of approximately 15.98 in MAE compared to GA-LSTM. This highlights the importance of relying on established methodologies like Base LSTM, which can outperform more complex optimization strategies in specific contexts, emphasizing the need for a nuanced understanding of the problem domain to effectively leverage innovative approaches like GA-LSTM.

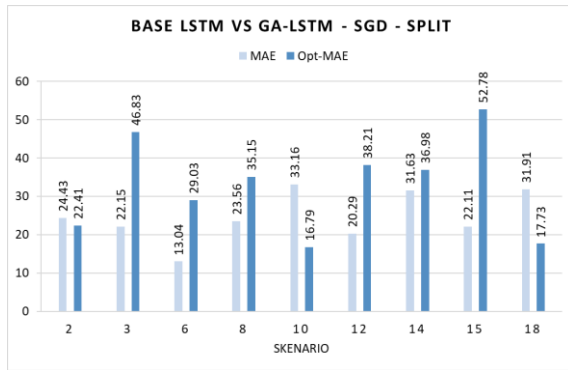


Figure 9. Comparison chart of Base LSTM vs GA-LSTM – SGD – Split

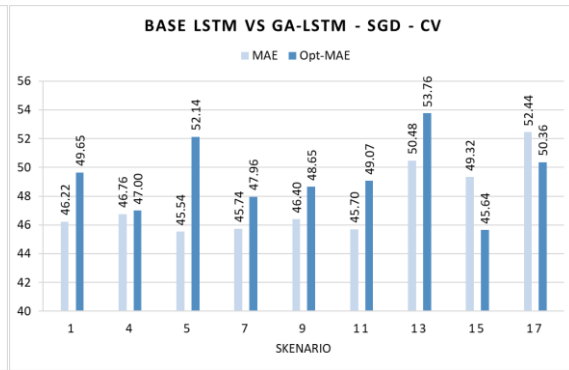


Figure 10. Comparison chart of Base LSTM vs GA-LSTM – SGD – Split

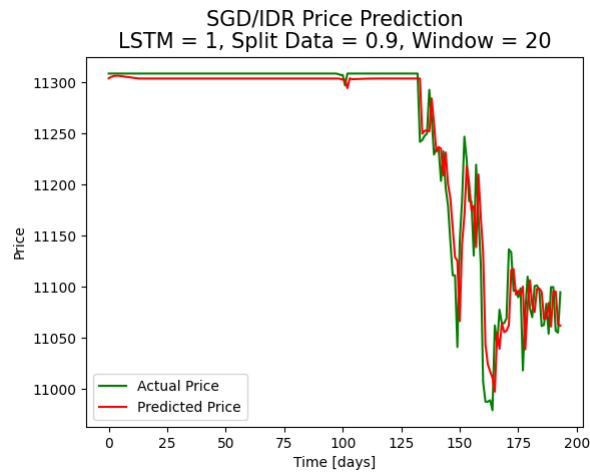


Figure 11. SGD Optimal Model Price Prediction

3.4 Forecasting Performance

Table 2. Model Performance in Test and Forecasting

Dataset	Model Optimal Performance	
	Test	Forecasting
USD	41.271	64.474
EUR	60.892	101.828
SGD	13.040	29.45

Based on Table 2, there is a noticeable contrast in the predictive performance between the USD and SGD models compared to the EUR model regarding short-term purchasing price predictions. While the USD and SGD models exhibit strong accuracy in forecasting these movements, the EUR model lags behind, indicating a need for improvement. The considerable difference between the optimal architecture and the forecasting ability of the EUR model, with a MAE gap of approximately 40.94, highlights the importance of reassessing and optimizing its parameters. Such steps are essential to improve its predictive precision and match the proficiency demonstrated by the USD and SGD models in capturing short-term currency price changes. Through meticulous parameter optimization, addressing these shortcomings could potentially narrow the gap and enhance the EUR model's effectiveness in forecasting currency prices over the short term.

4. Conclusion

The study reveals insights into the performance of LSTM models in forecasting foreign exchange rates. It underscores that while cross-validation tends to yield higher error values compared to data splitting, increasing the training data size or the number of folds does not consistently reduce LSTM model errors. However, optimization using Genetic Algorithms proves successful in reducing errors in certain scenarios.

For USD, the most effective LSTM model consists of three layers with varying cell counts, utilizing a sliding window approach and trained on 80% of the data. Conversely, for EUR, the optimal model comprises two layers with specific cell counts and is trained on 90% of the data. SGD data analysis indicates that a single-layer LSTM model with 128 cells and a sliding window of size 20, trained on 90% of the data, is the most optimal.

Notably, LSTM models exhibit accurate short-term predictions for USD and SGD against IDR, yet not for EUR. The study suggests avenues for further model refinement, including parameter variation, hybridization with other machine learning algorithms, and comparison with alternative time series prediction methods. Additionally, it advocates for exploring different optimization algorithms and incorporating external variables such as interest rates and economic indicators for enhanced predictive accuracy.

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