Jurnal Teknik Informatika (JUTIF) Vol. 7, No. 3, June 2026, Page. 2340-2349
P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2026. 7.3.5355

Comparative Analysis of Hyperparameter Optimization Methods for LSTM in Cryptocurrency Price Prediction: An Application to TRX–USD

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Received : Sep 29, 2025; Revised : Dec 4, 2025; Accepted : Jan 19, 2026; Published : Jun 15, 2026

Abstract

The rapid growth of cryptocurrencies increases the demand for accurate forecasting models to support investment decisions and automated trading systems. This study analyzes and compares the performance of several hyperparameter optimization methods applied to a Long Short-Term Memory (LSTM) model for predicting the price of TRX–USD. The dataset consists of 2,096 daily historical records obtained from the Binance platform, including open, high, low, close, volume, and percentage change, with the closing price selected as the forecasting target. A baseline LSTM model was evaluated against six optimization techniques: Grid Search, Random Search, Bayesian Optimization (Hyperopt), Optuna, Particle Swarm Optimization (PSO), and Genetic Algorithm (GA). Experimental results show that GA provides the best performance with an R^2 score of 0.88, MAE of 0.0123, RMSE of 0.0189, and a validation loss of 0.069. In contrast, Random Search yields the lowest performance, achieving an R^2 of only 0.2979. These findings highlight significant performance gaps among optimization strategies and demonstrate the superiority of metaheuristic-based approaches over conventional tuning methods. This research contributes to the advancement of computational intelligence by providing empirical evidence on the effectiveness of hyperparameter optimization techniques for deep learning–based time series forecasting, particularly in high-volatility financial environments.

Keywords : *Cryptocurrency Prediction, TRX/USD, Long Short-Term Memory (LSTM), Hyperparameter Optimization, Genetic Algorithm (GA)*

1. INTRODUCTION

The rapid growth of the cryptocurrency market has attracted great attention from researchers, investors, to policymakers. Unlike traditional financial assets, the price of cryptocurrencies is influenced by a variety of complex factors such as market sentiment, trading volume, as well as macroeconomic indicators, which makes the price forecasting process very challenging [1], [2], [3]. Among the different types of cryptocurrencies, TRON (TRX) has emerged as one of the most traded digital assets as well as has a significant role in the ecosystem of decentralized applications and blockchain-based financial services [4], [5], [6]. Based on data from TradingView, TRX is among the top 10 crypto assets with the most transaction activity in the world, occupying the 9th position. This fact shows that TRX is a very active, liquid, and relevant digital asset to be used as a case study. The high frequency of such transactions reinforces the reason for choosing TRX/USD in this study because the price prediction results of high-volume assets will have significant practical implications for trading strategies and risk management.

In the realm of machine learning, Long Short-Term Memory (LSTM) has proven to be superior in handling time series data that has long-term dependency [7], [8]. This model is widely used in stock price forecasting, energy, and digital currencies because of its ability to capture complex historical patterns [9], [10]. However, LSTM performance is greatly influenced by the selection of hyperparameters such as the number of neuron units, dropout rate, and learning rate [11]. Improper selection of hyperparameters can cause the model to underfit or overfit, thereby degrading the generalization ability of new data [12], [13].

Most previous research has focused on the use of LSTMs for cryptocurrency price prediction, but few have provided a comprehensive analysis of how hyperparameter optimization methods affect the model's performance [14], [15], [16], [17]. Conventional methods such as Grid Search and Random Search are often used, but they have limitations in terms of efficiency and exploration of a wide parameter space [18], [19]. In contrast, metaheuristic-based optimization approaches and modern algorithms such as Bayesian Optimization, Optuna, Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) offer better potential in finding optimal hyperparameter combinations with more efficient computational time [20], [21], [22].

Based on this background, this study aims to conduct a comparative analysis of various hyperparameter optimization methods on the LSTM model in predicting the price of TRX/USD. This study specifically compares the performance of Grid Search, Random Search, Bayesian Optimization, Optuna, PSO, and GA by considering evaluation metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 Score.

The main contribution of this study is to provide an in-depth understanding of the effectiveness of various hyperparameter optimization methods on the performance of LSTMs in the context of cryptocurrency price prediction. In addition, this research is expected to be a reference for artificial intelligence-based trading system developers and academics who focus on the topic of time series forecasting and financial technology.

2. METHOD

The methodology of this research is systematically designed to ensure that the analysis process runs in accordance with the set objectives. The research stage starts from dataset processing and preprocessing, followed by the construction of the LSTM baseline model, then hyperparameter optimization is carried out using various approaches, until the final stage in the form of model performance evaluation with predetermined metrics. Figure 1 below shows the flow of the research methodology used.

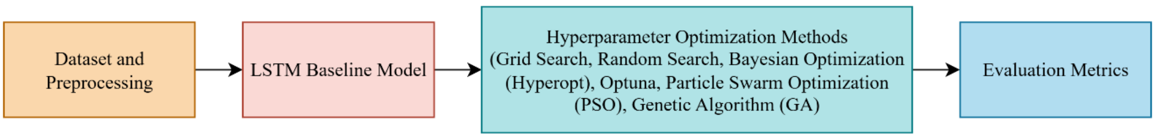

Figure 1. Research Methodology

Dataset and Preprocessing

The dataset used in this study consists of 2096 daily historical TRX/USD price data from the Binance platform. The available attributes include the transaction date, the opening price, the high price, the low price, the closing price/close, the trading volume (vol), and the percentage of daily price change (change). Out of all these attributes, the closing price is chosen as the target variable because it is widely considered to be the most relevant price representation in technical analysis, while the other attributes are used as supporting input variables. Statistical analysis shows that the price of TRX/USD has a minimum value of 0.00843 USD, a maximum of 0.4336 USD, with an average of 0.1036 USD and a standard deviation of 0.0814, which confirms a fairly high level of price volatility throughout the data period. Trading volumes recorded in units of million (M) or billion (B) as well as percentage price changes in percentage format require a pre-processing stage before they can be used further in the model.

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Overall, this dataset is considered representative for investigating the performance of LSTM models with various hyperparameter optimization methods in predicting TRX/USD price movements.

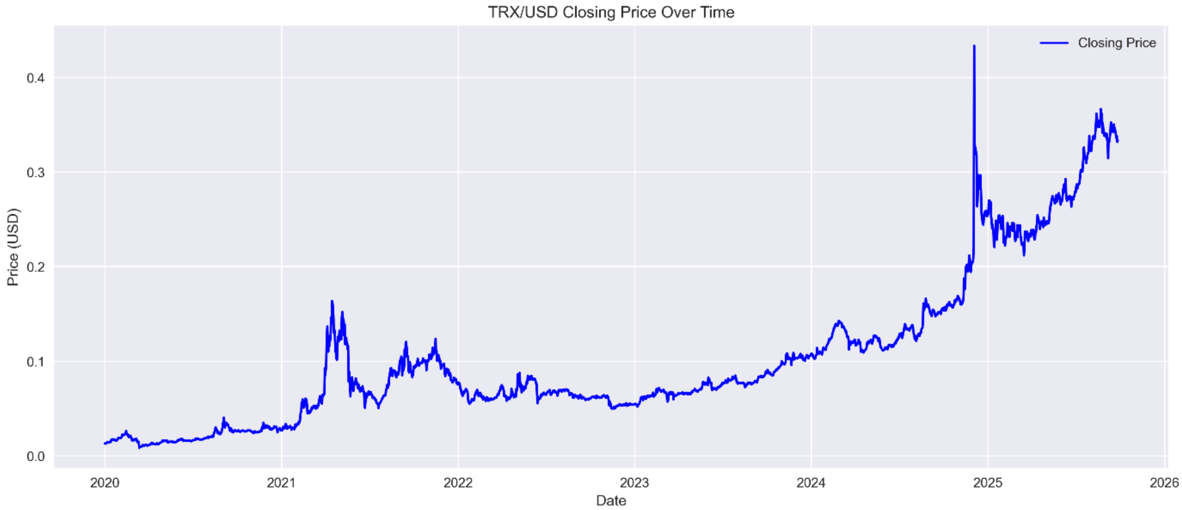

Figure 2. TRX/USD Closing Price Movement from 2019 to 2025

The pre-processing stage is carried out to ensure the quality of the data before use. This process includes cleaning of missing or anomalous values, normalization using *the Min-Max Scaler* so that all features are in the range [0,1], and the formation of *a sliding window* to produce a sequence of time series that corresponds to the characteristics of the LSTM. The dataset is then divided into three parts, namely 70% for *training*, 15% for *validation*, and 15% for *testing*.

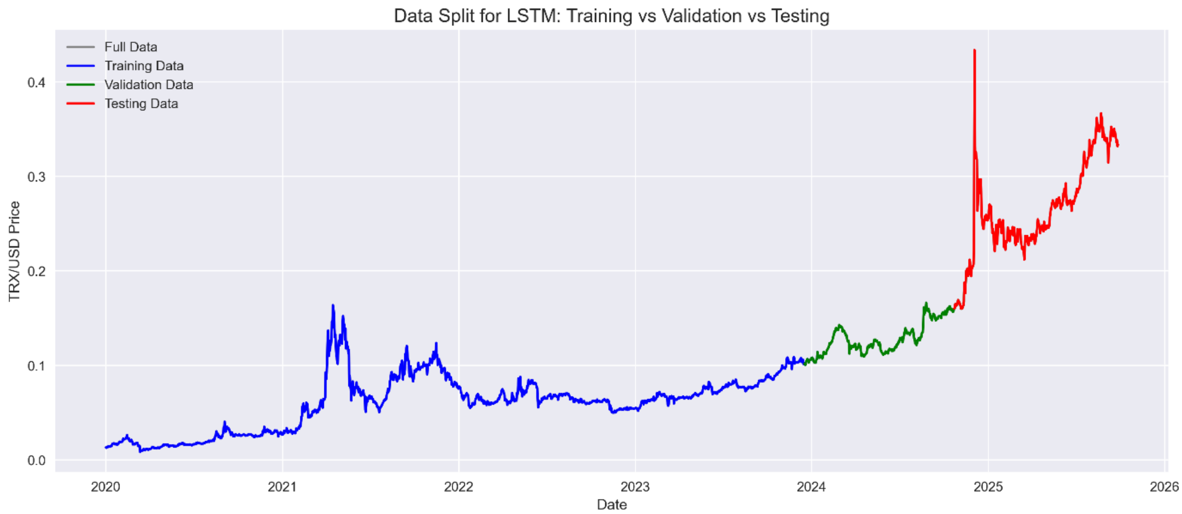

Figure 3. Splitting Data

LSTM Baseline Model

As a first step, a baseline model was built with the standard LSTM architecture consisting of a single LSTM layer, *a dropout* layer, and a *dense* layer to generate price predictions. This model was trained using *an Adam optimizer* with an initial *learning rate* of 0.001 and *Mean Squared Error (MSE)* as a loss function. The baseline results were used as a comparison in evaluating the effectiveness of the hyperparameter optimization method.

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Hyperparameter Optimization Methods.
Six hyperparameter optimization approaches were compared in this study, namely [22], [23], [24], [25], [26], [27]:

1. Grid Search – explores all predefined hyperparameter combinations.
2. Random Search – selects a combination of hyperparameters randomly in the search space.
3. Bayesian Optimization (Hyperopt) – uses the *Tree-structured Parzen Estimator approach* for adaptive exploration.
4. Optuna – a modern optimization library with *a flexible* define-by-run interface.
5. Particle Swarm Optimization (PSO) – a metaheuristic algorithm that mimics the behavior of a particle swarm.
6. Genetic Algorithm (GA) – an evolutionary algorithm based on natural selection, mutation, and *crossover*. Optimized hyperparameters include the number of LSTM units, *dropout rate*, and *learning rate*.

Evaluation Metrics
Model performance evaluation is carried out using several key metrics, namely [28], [29], [30], [31]:

1. Mean Absolute Error (MAE) to measure the mean of absolute error.
2. Root Mean Squared Error (RMSE) to calculate the average square root of the error.
3. R^2 Score to assess the degree of variation in data that the model can explain.
4. In addition, *validation loss* is also used as an indicator of performance during training.

The entire experiment was conducted using Python with *the TensorFlow/Keras library* for LSTM implementation. The hyperparameter optimization process is carried out using *scikit-learn* (Grid Search, Random Search), *Hyperopt*, *Optuna*, and *pymoo* for PSO and GA.

3. RESULT

The results of this study present the performance of the LSTM model in predicting the price of TRX/USD using various hyperparameter optimization methods. Evaluation was carried out using MAE, RMSE, R^2, and validation loss metrics. The baseline model was compared with six optimization methods, namely Grid Search, Random Search, Bayesian Optimization, Optuna, PSO, and GA. A summary of the results of the evaluation of all models is shown in Table 1 as the basis for comparing the effectiveness of each method.

Table 1. Evaluation Results

Method	Validation Loss (MSE)	IT IS	RMSE	R^2
Baseline	0.000136	0.0232	0.0283	0.5714
Grid Search	0.000138	0.0311	0.0340	0.3800
Random Search	0.000093	0.0320	0.0363	0.2979
Bayesian Opt.	0.000075	0.0240	0.0278	0.2656
Optuna	0.000066	0.0135	0.0195	0.7956
PSO	0.000070	0.0147	0.0203	0.7725
GA	0.000069	0.0123	0.0189	0.8088

Based on Table 1, it can be seen that there is a significant variation in performance between hyperparameter optimization methods. The baseline model showed a MAE value of 0.0232 and an RMSE of 0.0283 with an R^2 of 0.5714. This shows that LSTM is able to model TRX/USD price movement patterns, but its accuracy is still limited.

Conventional methods such as Grid Search and Random Search actually produce performance that is less good than the baseline. Grid Search only reaches R^2 at 0.3800, while Random Search is even

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lower at R^2 0.2979. This can be explained by the fact that the vast hyperparameter search space cannot be explored efficiently with brute force or random sampling approaches.

In contrast, adaptive and metaheuristic-based methods show much better results. Bayesian Optimization results in relatively low *validation loss*, but the R^2 value in the test data is only 0.2656, indicating an *overfitting* of the validation data. Optuna managed to significantly improve its performance with MAE 0.0135, RMSE 0.0195, and R^2 reaching 0.7956. PSO also showed a competitive result with R^2 0.7725. However, the best performance is shown by the Genetic Algorithm (GA), which reached a high R^2 of 0.8088 with an MAE of 0.0123 and an RMSE of 0.0189, making it the most effective method in optimizing the LSTM hyperparameter for TRX/USD price prediction.

Overall, these results confirm that metaheuristic approaches such as GA and PSO are able to provide better generalizations than conventional methods. Meanwhile, Optuna is emerging as an efficient modern alternative with performance close to GA. To provide a clearer picture of the predictability of each model, the results of the comparison between the actual value and the predicted value are shown in Figure 3, which shows how tight the prediction curve of the best model follows the actual price pattern of TRX/USD.

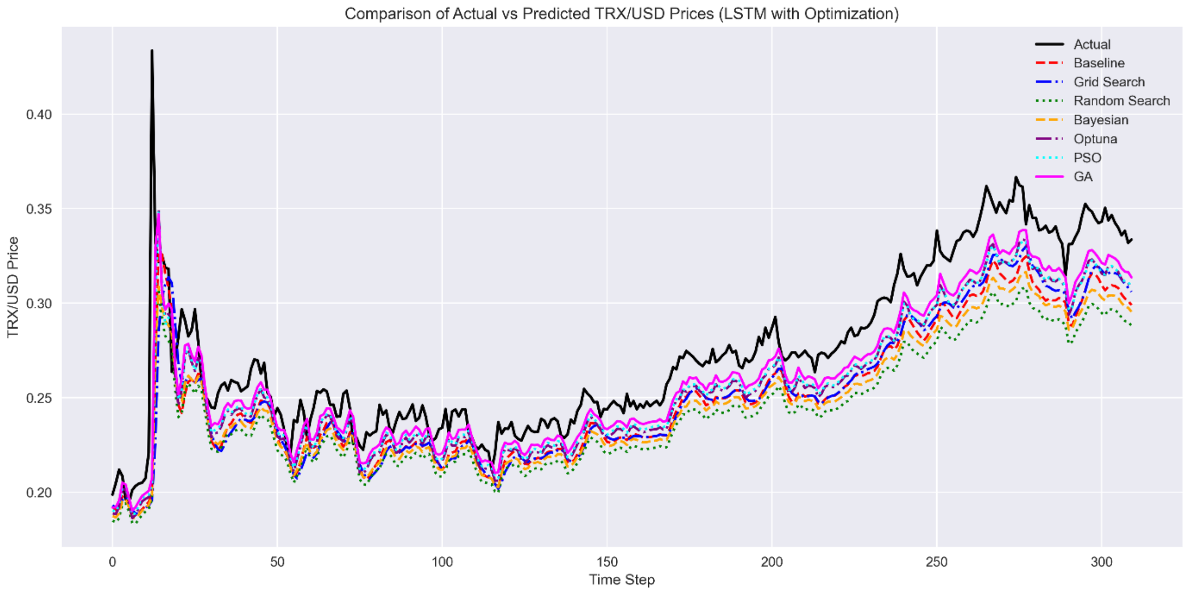

Figure 3. Comparison Chart Results

Figure 3 shows a comparison between the actual value of TRX/USD with the predicted results from the baseline LSTM model and six hyperparameter optimization methods. The black line represents actual data, while the colored line shows the predicted results of each model. From the visualization, it can be seen that most models manage to follow the general pattern of price movements, but there are differences in accuracy between methods.

Metaheuristic optimization-based models such as GA (magenta) and PSO (cyan), as well as modern approaches such as Optuna (purple) show prediction curves that are closest to the actual line. In contrast, conventional methods such as Grid Search (blue) and Random Search (green) result in greater deviations, especially during periods of sharp price fluctuations. This confirms the results of the quantitative evaluation in Table 1, where GA obtained the highest R^2 value, followed by Optuna and PSO.

To emphasize the best performance, Figure 4 shows the results of the Genetic Algorithm (GA) prediction compared to the actual value of TRX/USD. It can be seen that GA's prediction line is able to follow the actual price pattern very well, including sharp upward and downward trends. This shows that

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GA managed to find the optimal combination of hyperparameters, thereby improving the generalizability of the LSTM model in predicting cryptocurrency price movements.

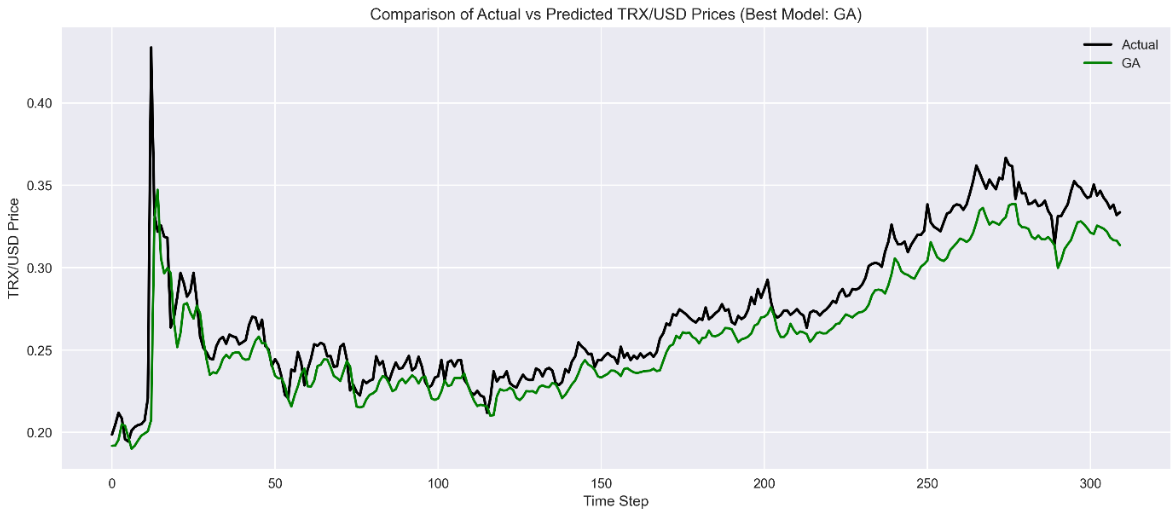

Figure 4. GA Results

Figure 4 shows a comparison between the actual price of TRX/USD and the prediction results generated by the LSTM model optimized using Genetic Algorithm (GA). It can be seen that the GA prediction line (green) is able to follow the actual price pattern (black) very well, both in the upward and downtrend phases. This degree of proximity confirms the results of previous quantitative evaluations (Table 1), in which GA obtained the highest R^2 score (0.8088) and the lowest prediction error. This confirms that GA is able to find optimal hyperparameter combinations, thus providing superior generalizations over other methods.

In contrast, to highlight the performance contrast, Figure 5 shows the predicted results of Random Search, which is the worst-performing method. From the graph it can be seen that although the Random Search prediction line (red) still follows the general direction of price movement, there is a considerable deviation from the actual line especially during periods of sharp fluctuations. This is consistent with the evaluation values in Table 1, where Random Search yields the lowest R^2 score (0.2979), indicating the limitations of this approach in exploring hyperparameter spaces effectively.

Figure 5 shows the results of a comparison between the actual price of TRX/USD and the LSTM model predictions optimized using Random Search. The dotted red line depicts the predicted outcome, while the black line indicates the actual price. It is seen that although Random Search is able to follow the general direction of price movements, considerable deviations occur especially in the phase of sharp fluctuations. This suggests that this method is less effective in finding optimal hyperparameter combinations, resulting in performance that is far below the best models such as GA. These findings are also in line with the quantitative evaluation in Table 1, where Random Search obtained the lowest R^2 score (0.2979) and relatively high prediction errors.

Overall, the results of this study show that the selection of hyperparameter optimization methods has a significant effect on the performance of LSTMs in predicting cryptocurrency prices. Conventional approaches such as Grid Search and Random Search have proven to be less efficient, while modern metaheuristic-based and optimization methods such as Genetic Algorithm (GA), Optuna, and PSO show substantial improvements in accuracy.

GA proved to be the best method with the highest evaluation value and prediction visualization that comes closest to actual data, while Random Search was the method with the lowest performance. These

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results provide empirical evidence that adaptive optimization strategies are superior in addressing the complexity of the LSTM hyperparameter space for TRX/USD price prediction.

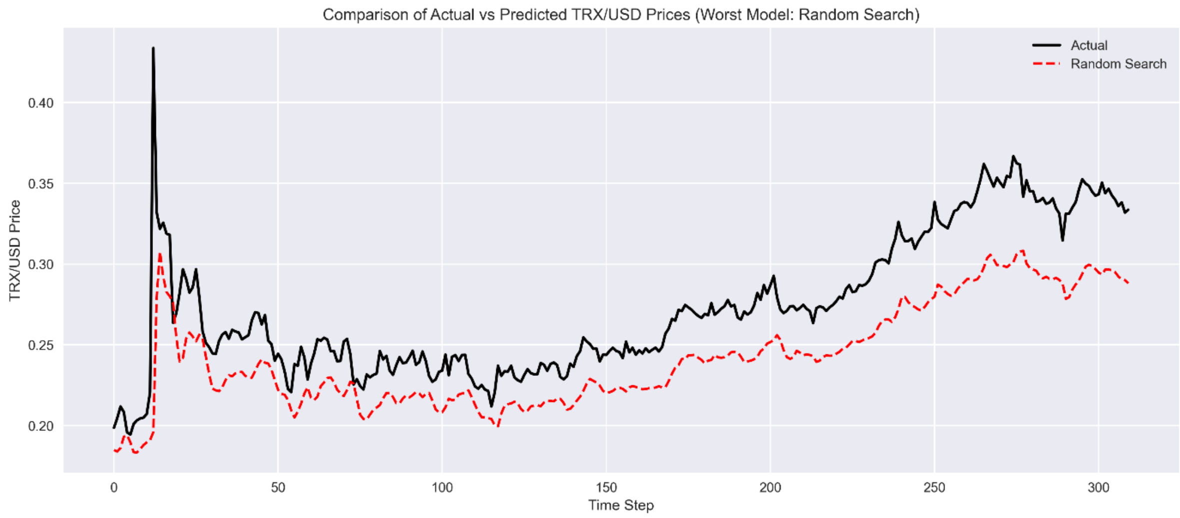

Figure 5. Random Search Results

4. DISCUSSIONS

The results of this study show that the selection of hyperparameter optimization methods has a significant effect on the performance of the LSTM model in predicting cryptocurrency prices. The evaluation in Table 1 shows that the Genetic Algorithm (GA) gives the best results with an R^2 of 0.8088 and the lowest prediction error value, while Random Search shows the worst performance with an R^2 of only 0.2979. This difference confirms that adaptive and metaheuristic optimization methods are superior to conventional approaches, especially in complex and high-dimensional hyperparameter spaces.

These findings are consistent with several studies emphasizing that hyperparameter optimization significantly enhances deep learning performance for financial time series forecasting. Kervanci et al. (2023) showed that tuning LSTM, GRU, and hybrid architectures using Bayesian Optimization, Random Search, and Grid Search improves prediction accuracy in Bitcoin price forecasting [23]. Similarly, Ulum and Girsang (2022) demonstrated that metaheuristic approaches such as the Symbiotic Organism Search algorithm can effectively optimize LSTM hyperparameters and reduce prediction errors in stock market forecasting [32]. Furthermore, Yildirim and Taskiran (2024) reported that modern optimization frameworks like Optuna enable deep learning models to better capture cryptocurrency price patterns, outperforming manually tuned configurations [33]. These studies reinforce the evidence observed in this research that adaptive and metaheuristic-based optimization methods generally achieve superior generalization compared to conventional tuning strategies in highly volatile financial environments.

From a practical perspective, the results of this study provide important implications for the digital finance industry. By utilizing the right optimization methods, the LSTM model can generate more reliable trading signals, support investment decision-making, and improve risk management in high-volatility assets such as TRX/USD. In particular, GA, Optuna, and PSO can be considered as promising optimization strategies in building artificial intelligence-based trading systems.

However, there are some limitations that need to be considered. This research dataset only focuses on historical data from one exchange (Binance), so the generalization of results still needs to be tested on cross-exchange data. In addition, the study only explored LSTMs, while other models such as the GRU or Transformer have the potential to provide better performance in certain scenarios. Therefore, further research can be directed towards testing more diverse models as well as a combination of multi-algorithm optimization to improve prediction robustness.

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Overall, these results reinforce the view that the integration of adaptive hyperparameter optimization methods into deep learning models is able to improve the performance of cryptocurrency price predictions. These findings not only support the current academic literature, but also open up wider practical implementation opportunities in the context of dynamic digital asset trading.

5. CONCLUSIONS

This study confirms that the selection of hyperparameter optimization methods plays an important role in improving the performance of the LSTM model for cryptocurrency price prediction. The case study on TRX/USD shows that modern metaheuristic-based methods and optimizations consistently outperform conventional approaches. Genetic Algorithm (GA) proved to be the best method with the highest accuracy and strong generalization, followed by Optuna and PSO, while Random Search was the method with the lowest performance. These results provide an empirical contribution that enriches the literature on the application of hyperparameter optimization in deep learning models for digital asset price forecasting.

In addition to making academic contributions, this research also has significant practical implications. Prediction models with optimal hyperparameters can support investors, trading system developers, and financial institutions in making more informed decisions and reducing risks in the highly volatile crypto market. However, there is still room for development, especially in the expansion of cross-exchange data and comparison with other architectures such as GRU or Transformer. Thus, further research is expected to expand the scope of experiments while testing the integration of various optimization methods to obtain more robust and applicable results in the context of dynamic digital financial markets.

This study shows the effectiveness of the hyperparameter optimization method in improving the performance of LSTM for cryptocurrency price prediction, specifically TRX/USD. However, there are several directions for further research that can be carried out. First, future research could expand the dataset to include more types of cryptocurrencies as well as a longer time span so that the predictive results have better generalizations. Second, alternative deep learning architectures such as GRU, Transformer, or hybrid models that combine CNN-LSTM can be explored to capture more complex temporal patterns. Third, the addition of external features such as macroeconomic indicators, investor sentiment, and blockchain network metrics has the potential to increase the accuracy of predictions. Finally, further experiments on the application of distributed training systems and real-time predictions can also be conducted to provide insights into the practical implementation of optimized LSTM models in real trading environments.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper. No financial or non-financial relationships exist between the authors and any parties that could have influenced the results or interpretation of this research.

ACKNOWLEDGEMENT

The authors would like to express their sincere gratitude to Telkom University for the support, facilities, and academic environment that made this research possible.

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P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
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