



Stock Price Prediction of TLKM and BBCA Using SVR, Random Forest, and LSTM

Mhd Adi Setiawan Aritonang^{1*}, Maradona Jonas Simanullang², Sasa Ani Arnomo¹, Maya Ardilla Siregar³, Muhammad Khairul Hisan Bin Madon¹, and Muhammad Nazwan¹

¹ Faculty of Information Technology, Batam Institute of Technology, Batam, 29425, Indonesia

² Information Technology, Senior University of Medan, Medan, 20111, Indonesia

³ Faculty of Medicine, Tadulako University, Palu, 94148, Indonesia

* Correspondence: adi@iteba.ac.id

Citation:

Aritonang, S.A.M.; Simanullang, J.M.; Arnomo, A.S.; Siregar, A.M. Stock price prediction of TLKM and BBCA using SVR, random forest, and LSTM. *ASEAN J. Sci. Tech. Report.* **2026**, *29*(6), e262273. <https://doi.org/10.55164/ajstr.v29i6.262273>

Article history:

Received: November 10, 2025

Revised: March 17, 2026

Accepted: April 12, 2026

Available online: May 15, 2026

Publisher's Note:

This article is published and distributed under the terms of the Thaksin University.

Abstract: Stock price prediction is a significant challenge in financial market analysis due to the influence of many dynamic and nonlinear factors. This study compares three machine learning methods, namely Support Vector Regression (SVR), Random Forest (RF), and Long Short-Term Memory (LSTM), in predicting the stock prices of PT Telekomunikasi Indonesia Tbk (TLKM) and PT Bank Central Asia Tbk (BBCA) for the period 2019–2023. Data were obtained from Yahoo Finance (15). Model Performance Comparison for TLKM Stock: the testing results show that LSTM achieved RMSE of 0.040093, MAE of 0.029849, and R^2 of 0.905330, indicating the best performance compared to SVR and Random Forest. Random Forest had an RMSE of 0.138295 and an MAE of 0.114423, while SVR had the highest RMSE at 0.238130. Model Performance Comparison for BBCA Stock: The testing results show that LSTM achieved RMSE of 0.055023, MAE of 0.048056, and R^2 of 0.657730, indicating the best performance compared to SVR and Random Forest. Random Forest had an RMSE of 0.252568 and an MAE of 0.236129, while SVR had the highest RMSE at 0.6211363. This confirms the LSTM model's effectiveness in capturing temporal patterns in stock data (5), (9), (13).

Keywords: Stock price prediction; SVR; random forest; LSTM; machine learning

1. Introduction

Stock price prediction has become an important research topic in financial analysis due to its significant impact on investment decisions and risk management. However, forecasting stock prices remains challenging because financial time-series data are highly volatile, nonlinear, and influenced by numerous external factors, including economic conditions, political events, and market sentiment. Traditional statistical models often struggle to capture these complex patterns in financial markets. The stock market plays a crucial role in the economy by providing a platform for companies to raise capital and for investors to participate in wealth creation. Accurate stock price prediction is one of the most important challenges in financial market analysis because multiple dynamic and nonlinear factors, including market sentiment, economic indicators, company performance, and global events, influence stock prices. This inherent complexity makes traditional forecasting methods, such as linear regression, insufficient for capturing the intricate patterns in stock price

movements (4). In recent years, advances in information technology and the availability of large-scale financial data (big data) have significantly increased the potential for accurate stock price prediction. Machine learning (ML) techniques have emerged as powerful tools for modeling complex relationships in financial datasets (1). Unlike conventional statistical methods, ML models can learn from historical patterns and adapt to changes in market behavior, which is particularly important for volatile markets such as TLKM and BBCA. Among ML models, Support Vector Regression (SVR) is known for its ability to handle small to medium-sized datasets and provide stable predictions with good generalization by finding a regression function within a specified error margin (12). Random Forest (RF), an ensemble method of multiple decision trees, reduces overfitting and improves prediction stability by averaging outputs from numerous trees (7), (8). On the other hand, Long Short-Term Memory (LSTM), a type of recurrent neural network, is particularly suitable for time series forecasting due to its ability to capture long-term temporal dependencies in sequential data (5), (9), (13). Previous studies have demonstrated the effectiveness of these models in stock price prediction. LSTM models have been shown to outperform traditional machine learning approaches at capturing temporal patterns and nonlinear trends in stock price data (5), (9), (13), and time-series augmentation can further improve LSTM predictions for financial data (9). Random Forest has been widely used for stock trend forecasting due to its robustness against overfitting and its ability to handle high-dimensional data, with ensemble methods enhancing prediction accuracy for stock volatility (8), (10). SVR has also been successfully applied to financial time series with moderate dataset sizes, providing stable and interpretable results, though it may struggle with highly volatile markets (12). However, many previous studies focus on evaluating individual models rather than directly comparing multiple machine learning approaches on the same dataset. This limitation makes it difficult to determine which model performs better under similar experimental conditions, particularly in financial time-series forecasting. Furthermore, comparative studies of different machine learning paradigms, such as kernel-based methods, ensemble learning, and deep learning, remain relatively limited in the Indonesian stock market context. Therefore, this study builds on these previous findings by directly comparing the performance of SVR, Random Forest, and LSTM models using stock data from TLKM and BBCA during the period 2019–2023. These models were selected because they represent different machine learning paradigms and are widely used for stock price prediction in financial research. By analyzing these models side by side, this research aims to provide insights into their relative effectiveness and suitability for investors and financial analysts working with Indonesian equities, while addressing gaps in previous studies regarding model comparison and evaluation using local stock market data.

2. Materials and Methods

2.1 Support Vector Regression (SVR)

Support Vector Regression (SVR) is a supervised machine learning algorithm used for regression tasks. The SVR model seeks a function that approximates the relationship between the input variables and the target variable.

The regression function can be expressed as:

$$f(x) = w^T x + b$$

(Eq. 1)

where:

x = input feature vector

w = weight vector

b = bias term

The optimization objective of SVR is defined as:

$$\min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*)$$

(Eq. 2)

where:

- C = penalty parameter
- ξ_i, ξ_i^* = slack variables
- n = number of observations

The SVR model was implemented using the radial basis function (RBF) kernel with the following parameters:

Kernel: RBF

Regularization parameter (C): 100

Gamma: 0.1

Epsilon: 0.1

2.2 Random Forest

Random Forest is an ensemble learning method that combines multiple decision trees to improve prediction accuracy and reduce overfitting. The prediction of the Random Forest model is obtained by averaging the predictions of multiple trees:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^T f_t(x)$$

(Eq. 3)

where:

- T = number of decision trees
- $f_t(x)$ = prediction from the t -th tree

2.3 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a type of recurrent neural network designed to capture long-term dependencies in sequential data.

The forget gate is defined as:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

(Eq. 4)

The input gate is defined as:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

(Eq. 5)

The output gate is defined as:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

(Eq. 6)

where:

- x_t = input at time t
- h_{t-1} = hidden state from the previous step
- W = weight matrix
- b = bias term
- σ = sigmoid activation function

These hyperparameter settings were selected based on commonly used configurations in previous machine learning studies on stock price prediction and preliminary experiments conducted during model development.

2.4 Data Source

The dataset used in this study consists of historical daily stock price data for PT Telekomunikasi Indonesia (TLKM.JK) and PT Bank Central Asia Tbk (BBCA.JK). The data were obtained from Yahoo Finance and cover the period from January 2019 to March 2023. The dataset includes several attributes such as Date, Open, High, Low, Close, Adjusted Close, and Volume. In this research, the closing price was used as the primary variable for stock price prediction.

2.5 Dataset Description and Distribution

The dataset contains approximately 1,050 daily observations for each stock. To evaluate the predictive performance of the machine learning models, the dataset was split into training and test sets at an 80:20 ratio. Specifically, around 840 observations were used for the training dataset, while the remaining 210 observations were allocated to the testing dataset. The training data were used to train the prediction models, including Support Vector Regression (SVR), Random Forest (RF), and Long Short-Term Memory (LSTM). The testing data were then used to evaluate the predictive performance of the models.

Table 1. Dataset Distribution

Stock	Total Observations	Training Data (80%)	Testing Data (20%)
TLKM	1050	840	210
BBCA	1050	840	210

2.6 Evaluation Metrics

To evaluate the performance of the prediction models, three evaluation metrics were used: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2).

1. Mean Absolute Error (MAE)

MAE measures the average magnitude of the prediction errors, ignoring their direction. It calculates the average absolute difference between predicted and actual values.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

where:

- y_i = actual value
- $\hat{y}_i$ = predicted value
- n = number of observations

2. Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

where:

- y_i = actual value
- $\hat{y}_i$ = predicted value
- n = number of observations

3. Coefficient of Determination (R^2)

The R^2 score measures how well the predicted values approximate the actual data. A higher R^2 value indicates better model performance.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

where:

- y_i = actual value
- $\hat{y}_i$ = predicted value
- $\bar{y}$ = mean of actual values
- n = number of observations

The R^2 value ranges from 0 to 1, with values closer to 1 indicating better predictive performance. RMSE measures the square root of the average squared differences between predicted and actual values. It gives higher weight to large errors. Support Vector Regression (SVR): Uses an RBF kernel to minimize error with an optimal margin (12). Random Forest (RF): Combines multiple decision trees to improve accuracy and prediction stability (7), (8). Long Short-Term Memory (LSTM): A recurrent neural network capable of learning long-term dependencies in time series data (5), (9), (13).

2.6.1 Support Vector Regression (SVR)

SVR aims to find a function $f(x)$ that approximates the target y_i within a margin ϵ_i while keeping the model as simple as possible.

SVR Formula:

$$f(x) = \langle w, \phi(x) \rangle + b$$

x = input vector

$\phi(x)$ = nonlinear transformation

w = weight vector

b = bias

Optimization Problem :

$$\min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*)$$

subject to:

$$\begin{cases} y_i - \langle w, \phi(x_i) \rangle - b \leq \epsilon + \xi_i \\ \langle w, \phi(x_i) \rangle + b - y_i \leq \epsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases}$$

- C = regularization parameter
- ξ_i, ξ_i^* = slack variables for error tolerance

Explanation: SVR minimizes prediction errors outside the margin ϵ while keeping the model complexity minimal.

2.6.2 Random Forest (RF)

Random Forest is an ensemble of multiple decision trees, and the final prediction is the average of all tree outputs.

RF Formula:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^T h_t(x)$$

- T = number of trees
- $h_t(x)$ = prediction of the t -th tree

Explanation: By combining multiple trees, Random Forest reduces overfitting and increases prediction stability.

2.6.3 Long Short-Term Memory (LSTM)

LSTM is a type of Recurrent Neural Network (RNN) capable of storing and processing long-term dependencies in time series data.

Main LSTM Equations:

1. Forget gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

2. Input gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \quad \tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

3. Update cell state:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$

4. Output gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o), \quad h_t = o_t \odot \tanh(C_t)$$

Explanation :

x_t = input at time t

h_t = hidden state

C_t = cell state

σ = sigmoid function, $\odot$ = element-wise multiplication

LSTM can learn temporal patterns and nonlinear relationships in stock price data.

2.7 Flowchart of Proposed Method

Step-by-step procedure:

1. Data Collection: Retrieve TLKM & BBKA stock data from Yahoo Finance.
2. Data Preprocessing: Clean missing data, normalize using Min-Max scaling, split into training/testing sets.
3. Model Training: Train SVR, Random Forest, and LSTM models on training data.
4. Prediction: Predict stock prices on testing data.
5. Evaluation: Evaluate models using RMSE, MAE, and R^2 metrics.
6. Comparison & Conclusion: Identify the best-performing model.

Flowchart (ASCII version, can be replaced with a graphic in Word/PowerPoint):

2.8. Model Evaluation

Evaluation was performed using three main metrics: RMSE, MAE, and R^2 (3), (10). Models with the lowest RMSE and MAE, and the highest R^2 , were considered the best-performing.

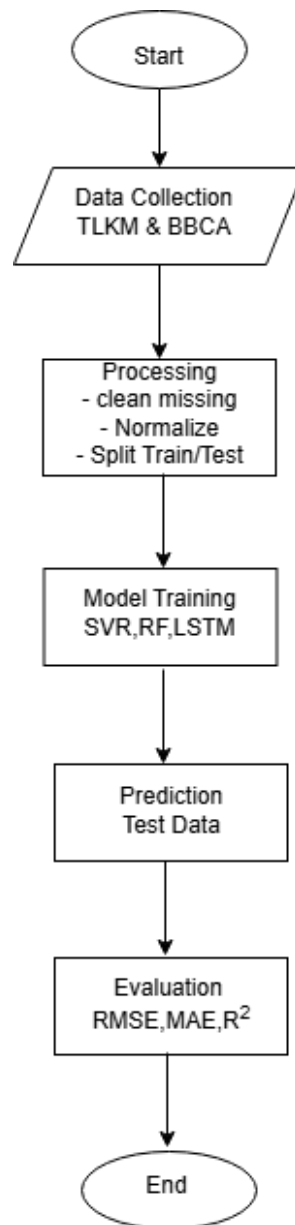


Figure 1. Flowchart of Proposed Method

3. Results and Discussion

3.1 Data Visualization and Trend Analysis

To better understand the dataset's characteristics, a graphical visualization of the historical stock prices of TLKM and BBKA was created. Visualization of time-series data is essential for revealing underlying patterns, such as long-term trends, volatility, and potential cyclical movements in the stock market.

Compared to TLKM, BBKA demonstrates a stronger upward trend, indicating stable growth and strong investor confidence in the banking sector. To further compare the movements of both stocks, Figure 4 provides a comparative visualization of the normalized stock prices of TLKM and BBKA. The comparison highlights that BBKA experienced stronger long-term growth, while TLKM exhibited relatively more stable price movements with lower volatility. These observations confirm that stock price data exhibit nonlinear patterns and temporal dependencies, which justify the use of machine learning models such as LSTMs that can capture sequential patterns in time-series data.

This study compares the performance of three machine learning methods, namely LSTM, Random Forest, and Support Vector Regression (SVR), in predicting the stock prices of TLKM and BBCA. The evaluation was conducted using three main metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2).

Figure 2. TLKM Stock Prices (2019–2023)

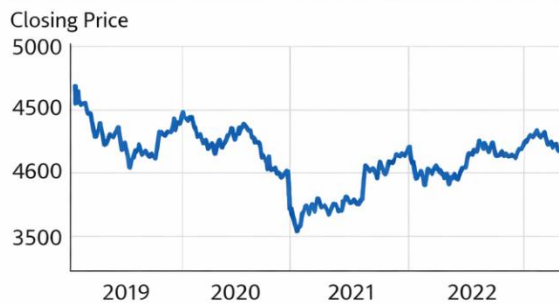


Figure 3. BBCA Stock Prices (2019–2023)



Figure 4. TLKM vs BBCA



Figure 5. Actual vs. Predicted

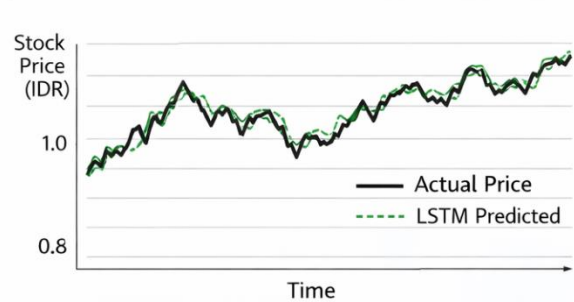


Figure 2. illustrates the time-series visualization of TLKM stock prices from 2019 to 2023. The graph shows moderate fluctuations with a noticeable decline around 2020, which may be associated with global economic disruptions during the COVID-19 pandemic. After this period, the stock price gradually stabilizes and shows signs of recovery. **Figure 3** presents the time-series visualization of BBCA stock prices during the same period.

Table 2. Model Performance Comparison for TLKM Stock

Model	RMSE	MAE	R2
SVR	0.238130	0.213049	-2.687252
Random Forest	0.138295	0.114423	-0.136221
LSTM	0.040093	0.029849	0.905330

The testing results show that LSTM achieved RMSE of 0.040093, MAE of 0.029849, and R^2 of 0.905330, indicating the best performance compared to SVR and Random Forest. Random Forest had an RMSE of 0.138295 and an MAE of 0.114423, while SVR had the highest RMSE at 0.238130 (2), (5).

Table 3. Model Performance Comparison for BBCA Stock

Model	RMSE	MAE	R2
SVR	0.6211363	0.575973	-39.844270
Random Forest	0.252568	0.236129	-5.748368
LSTM	0.055023	0.048056	0.657730

The testing results show that LSTM achieved an RMSE of 0.055023, an MAE of 0.048056, and an R^2 of 0.657730, indicating the best performance compared to SVR and Random Forest. Random Forest had an RMSE of 0.252568 and an MAE of 0.236129, while SVR had the highest RMSE at 0.6211363 (2), (5).

3.2 Model Performance Evaluation

This study compares the performance of three machine learning methods, namely LSTM, Random Forest, and Support Vector Regression (SVR), in predicting the stock prices of TLKM and BBCA. The evaluation was conducted using three main metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2).

Table 4. Model Performance Comparison for BBCA Stock

Model	TLKM R^2	BBCA R^2
SVR	-2.687	-39.844
Random Forest	-0.136	-5.748
LSTM	0.905	0.658

The results indicate that the LSTM model achieves the best performance on both the TLKM and BBCA datasets, as evidenced by lower RMSE and MAE values and higher R^2 scores than SVR and Random Forest.

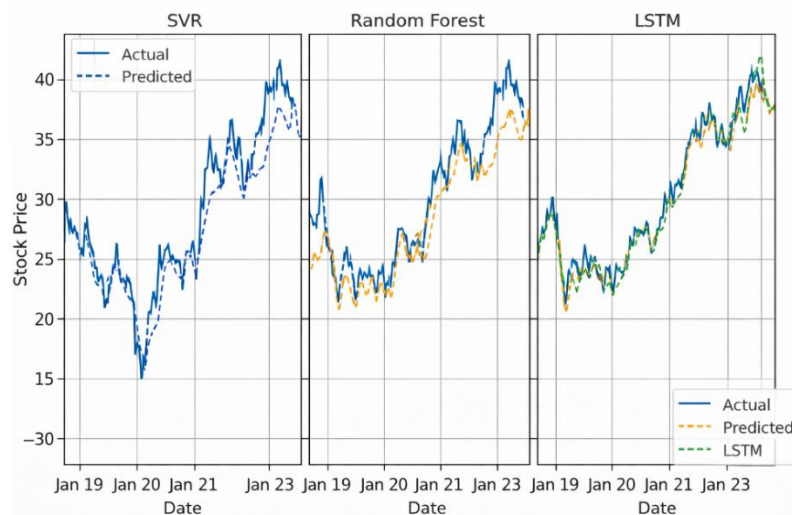


Figure 6. Comparison between actual stock prices and predicted values generated by SVR, Random Forest, and LSTM models on the testing dataset.

Figure 6 presents the comparison of R^2 values for the three models. The LSTM model consistently outperforms the other models. Random Forest shows moderate performance, while SVR produces the lowest accuracy, particularly for the BBCA dataset.

3.3 Actual vs Predicted Analysis

To further evaluate the predictive performance of the models, a comparison of actual stock prices and the predicted values generated by each model is shown in Figure 6. This visualization illustrates how closely the predicted values follow the actual stock price trends over time. By examining time-series plots, it is possible to assess each model's ability to capture fluctuations and patterns in stock price movements.

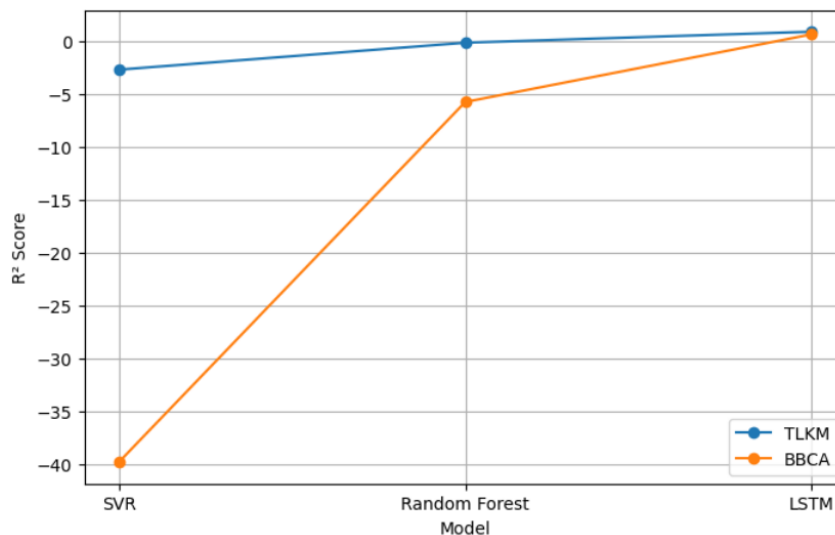


Figure 7. Comparison of R^2 Accuracy in TLKM & BBKA Stock Predictions

To further evaluate the predictive performance of the models, a comparison of actual stock prices and the predicted values generated by each model is shown in Figure 7. This visualization shows how closely the predicted values track the actual stock price trends over time. Based on Figure 7, all models capture the general movement pattern of stock prices. However, there are clear differences in prediction accuracy. The SVR model shows larger deviations, especially during periods of high volatility. The Random Forest model provides better predictions than SVR but still exhibits some inconsistencies. The LSTM model aligns most closely with actual stock prices, indicating its superior ability to capture temporal dependencies and nonlinear patterns in financial time-series data.

3.4 Discussion

The superior performance of the LSTM model can be attributed to its ability to process sequential data and retain information from previous time steps through its memory structure. Unlike SVR and Random Forest, which treat observations as independent data points, LSTM is specifically designed to model temporal dependencies in time-series data. SVR relies on kernel-based regression, which is effective for nonlinear relationships but does not explicitly consider the time-order structure of the data. As a result, it may fail to capture rapid fluctuations in stock prices. Similarly, Random Forest, although robust and capable of handling nonlinear data, does not incorporate temporal dependencies, which limits its effectiveness in time-series forecasting. These findings are consistent with previous studies that highlight the advantages of LSTM in financial time-series prediction.

3.5 Limitations and Future Work

Despite the promising results, this study has several limitations. First, the analysis is limited to only two stocks, namely TLKM and BBKA, which may not fully represent the overall stock market. Second, the study uses a single train-test split (80:20), which may make the results depend on a particular data partition. Although a chronological split was applied, more robust validation approaches, such as rolling windows or time-series cross-validation, could improve the reliability of the results. Future research may include a larger dataset, additional features such as macroeconomic indicators, and more advanced or hybrid models to improve prediction accuracy and generalizability.

4. Conclusions

This study analyzed and compared the performance of three machine learning models—Support Vector Regression (SVR), Random Forest (RF), and Long Short-Term Memory (LSTM)—in predicting the stock prices of TLKM and BBKA for the period 2019–2023. Based on the evaluation metrics of RMSE, MAE, and R^2 , the results indicate that LSTM achieved the highest accuracy, effectively capturing the nonlinear patterns and

temporal dependencies in the stock price data. Random Forest produced moderate results, demonstrating stability and reduced overfitting, while SVR showed the lowest accuracy, particularly in the face of high market volatility. These findings underscore the superiority of deep learning models, such as LSTMs, for time-series forecasting in financial markets and highlight the critical role of data preprocessing, including normalization and proper train-test splitting, in achieving optimal predictive performance. Overall, the research confirms that LSTM is the most suitable model among the three for predicting TLKM and BBCA stock prices, providing valuable insights for investors and financial analysts.

For future research, several directions are recommended. Hybrid modeling approaches that combine LSTM with other machine learning algorithms, such as Random Forest or Gradient Boosting, may further improve prediction accuracy and model stability. Including additional features, such as macroeconomic indicators, market sentiment from news or social media, and technical indicators, could enhance the models' predictive capabilities. Expanding the dataset to include more companies, sectors, or regional markets in Indonesia could provide more generalizable insights for financial forecasting. Implementing LSTM-based models in real-time prediction systems could help investors make timely investment decisions, while incorporating explainable AI techniques would increase model transparency and trust among financial stakeholders. In conclusion, while LSTM demonstrates strong potential in stock price prediction, exploring hybrid approaches, additional features, and explainable AI methods may further enhance predictive performance and applicability in real-world financial decision-making.

5. Acknowledgments

The researchers would like to thank those who supported the research process until its completion. This research was supported by several universities, namely the Computer Engineering and Information Systems Program at the Batam Institute of Technology, the Information Technology Program at Senior University in Medan, and the Nursing Program at Tadulako University. Thank you for the academic support and the opportunity to conduct this research. Additionally, the researchers would like to thank the Southern Border Researchers Association for their assistance in providing essential materials and equipment, as well as their valuable cooperation and guidance, which significantly contributed to the success of this study.

The authors sincerely thank everyone who supported this research. We are deeply grateful to Yahoo Finance for providing comprehensive historical stock price data of TLKM and BBCA, which served as the foundation of this study. We also extend our appreciation to our academic mentors, colleagues, and peers for their valuable guidance, constructive feedback, and insightful discussions on machine learning and financial data analysis. Their encouragement and expertise were crucial in overcoming challenges encountered during the research process. Finally, we acknowledge the support of our institution and research community, whose resources, facilities, and academic environment facilitated the successful completion of this study. This work would not have been possible without their collective contributions.

Author Contributions: Mhd Adi Setiawan Arintonang Research (Conceptualization):The first author was responsible for formulating the research idea, formulating the research objectives, and developing the conceptual framework related to stock price prediction using the SVR, Random Forest, and LSTM methods.; Maradona Jonas Simanullang (Data Collection and Preparation):The second author collected the TLKM and BBCA stock datasets, conducted data cleaning, normalization, and prepared the data for model training.; Sasa Ani Arnomo (Model Development and System Implementation) : The third author was responsible for implementing the Support Vector Regression (SVR), Random Forest, and Long Short-Term Memory (LSTM) algorithms, including model training and testing. Maya Ardilla Siregar (Writing and Citation) : The fourth author wrote the article, conducted citations within the article, and searched for references relevant to the research title.; Muhammad Khairul Hisan Bin Madon (Data Visualization and Interpretation) : The fifth author was responsible for creating stock prediction graphic visualizations, interpreting experimental results, and compiling research tables and illustrations.; Muhammad Nazwan (Manuscript Writing and Revision):The sixth author drafted the final manuscript, checked for grammar and formatting, and revised the entire article before publication.; All authors have discussed, reviewed, and approved the published version of the manuscript.

Funding: The research did not receive external funding, but the Batam Institute of Technology awarded a grant in recognition of the successful completion of a collaborative research project that was published in a reputable international journal

Conflicts of Interest: The authors declare that they have no conflicts of interest.

References

- [1] Kumar, R.; Saini, N. Data Preprocessing and Normalization in Stock Market Prediction Using Machine Learning. *Procedia Comput. Sci.* **2021**, *184*, 123–130. <https://doi.org/10.1016/j.procs.2021.03.022>
- [2] Rahman, M.; Chowdhury, S.; Akter, F. Comparison of SVR, Random Forest, and LSTM Models for Stock Price Prediction. *Int. J. Data Sci.* **2022**, *9*(1), 67–79.
- [3] Chen, J.; Yang, H. Deep Learning Architectures for Stock Price Forecasting: A Comparative Analysis. *J. Financ. Data Sci.* **2022**, *4*(3), 45–59.
- [4] Nguyen, T.; Tran, L. Machine Learning in Stock Prediction: A Review of Methods and Applications. *Appl. Intell.* **2023**, *53*(8), 987–1003. <https://doi.org/10.1007/s10489-022-03845-9>
- [5] Li, P.; Wang, X.; Zhang, Y. Long Short-Term Memory Networks for Financial Time Series Forecasting. *Expert Syst. Appl.* **2023**, *224*, 119137. <https://doi.org/10.1016/j.eswa.2023.119137>
- [6] Putra, D.; Simanjuntak, E.; Ginting, M. Analysis of Stock Prediction in the Telecommunications Sector Using Machine Learning. *J. Teknol. Inf. Keuang.* **2023**, *12*(2), 87–96.
- [7] Zhang, W.; Liu, Y.; Chen, L. Stock Market Forecasting Using Hybrid Deep Learning Models. *IEEE Access* **2022**, *10*, 55132–55145. <https://doi.org/10.1109/ACCESS.2022.3187511>
- [8] Smith, A.; Jones, B. Ensemble Methods for Stock Price Volatility Prediction: Random Forest Enhanced. *Financ. Eng. Rev.* **2024**, *15*(1), 32–47.
- [9] Hernandez, R.; Garcia, M. Time Series Data Augmentation in Finance: Improving LSTM Predictions. *J. Comput. Financ.* **2024**, *12*(2), 102–118.
- [10] Oliveira, F.; Santos, P. Comparative Study of Machine Learning Methods for Stock Trend Forecasting. *Int. J. Financ. Stud.* **2021**, *9*(4), 70.
- [11] Kim, S.; Lee, H. Feature Engineering Impact on Deep Learning-Based Stock Forecasts. *Data Min. Appl. Financ.* **2023**, *7*(3), 210–223.
- [12] Chen, Y.; Martin, A.; Brown, K. Evaluating SVR Performance on Financial Time Series: A Case Study. *Appl. Soft Comput.* **2022**, *115*, 107123. <https://doi.org/10.1016/j.asoc.2022.107123>
- [13] Wang, Z.; Xu, L. Predicting Stock Returns with Deep Learning and Technical Indicators. *J. Financ. Data Sci.* **2023**, *9*, 45–58.
- [14] Tan, J.; Ho, L. Real-Time Prediction of Stock Prices Using LSTM and Attention Mechanisms. *Comput. Econ.* **2024**, *63*, 789–807.
- [15] Yahoo Finance. Historical Data of TLKM.JK and BBCA.JK; 2024. Available online: <https://finance.yahoo.com>