# Multivariate Stock Price Forecasting Using Bidirectional Long Short-Term Memory (BiLSTM) with Technical Indicators

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## ABSTRACT

Stock price forecasting has become an important research area in financial market analysis due to the highly dynamic and volatile nature of stock market movements. Accurate forecasting models can assist investors and financial analysts in making better investment decisions and managing financial risks more effectively. This study proposes a Bidirectional Long Short-Term Memory (BiLSTM)-based deep learning model for forecasting stock prices using multivariate financial time-series data. The dataset used in this study consists of historical stock market data combined with several technical indicators, including High, Low, Open, Volume, Moving Average (MA10 and MA20), and Relative Strength Index (RSI). Prior to model training, the data underwent preprocessing stages including data cleaning, normalization, and sequence generation using a sliding window approach. The proposed architecture employs a Bidirectional LSTM layer followed by additional LSTM and dense layers to capture complex temporal dependencies and nonlinear patterns in stock price movements. The experimental results demonstrate that the proposed model achieved moderate forecasting performance with an MAE value of 15.5805, RMSE of 21.0883, and $R^2$ score of 0.4954. Furthermore, the prediction results show that the model was able to follow the general trend of actual stock price movements despite several deviations during periods of high market volatility. The findings indicate that the BiLSTM architecture has strong potential for financial time-series forecasting and can effectively capture important sequential patterns in stock market data. This study also highlights the challenges of stock price prediction due to the stochastic and nonlinear behavior of financial markets. Future research is recommended to incorporate additional external factors and more advanced deep learning architectures to further improve forecasting accuracy and robustness.

**Keywords** Stock Price Forecasting, Bidirectional LSTM (BiLSTM), Deep Learning, Financial Time Series, Technical Indicators

Submitted 22 November 2025
Accepted 15 February 2026
Published 22 August 2026

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DOI: 10.47738/ijrm.v3i3.70



## INTRODUCTION

Stock price forecasting has become one of the most important research topics in financial market analysis due to the highly dynamic, nonlinear, and volatile behavior of stock market movements [1]. Accurate forecasting models are essential for investors, financial analysts, and institutions to support investment decision-making, portfolio management, and risk mitigation strategies [2]. However, predicting stock prices remains a significant challenge because financial markets are influenced by multiple complex factors, including historical price behavior, trading volume, macroeconomic conditions, investor sentiment, and unexpected global events. Traditional statistical forecasting approaches, such as Autoregressive Integrated Moving Average (ARIMA) and linear

**How to cite this article:** E. G. Golacka, "Multivariate Stock Price Forecasting Using Bidirectional Long Short-Term Memory (BiLSTM) with Technical Indicators," *Int. J. Res. Metav.*, vol. 3, no. 3, pp. 223-238, 2026.

regression models, have been widely used for stock market prediction. Nevertheless, these conventional methods often struggle to capture nonlinear relationships and long-term temporal dependencies within financial time-series data, resulting in limited forecasting performance, particularly during periods of high market volatility [3].

In recent years, deep learning techniques have gained increasing attention in financial forecasting research because of their superior capability in learning complex nonlinear patterns from large-scale sequential data. Among various deep learning methods, Long Short-Term Memory (LSTM) networks have shown promising performance for time-series forecasting tasks due to their ability to overcome the vanishing gradient problem commonly found in traditional Recurrent Neural Networks (RNN). LSTM models are capable of storing long-term dependencies and extracting temporal information from historical stock price data more effectively [4]. Several previous studies have successfully applied LSTM-based models for stock price prediction and reported improvements in forecasting accuracy compared to traditional machine learning and statistical methods. Furthermore, recent advancements in Bidirectional Long Short-Term Memory (BiLSTM) architectures have demonstrated better capability in capturing sequential information from both forward and backward temporal directions, thereby improving contextual understanding and prediction stability [5].

Despite the promising performance of deep learning approaches, several limitations and research gaps still exist in current stock forecasting studies. First, many previous studies primarily focused on univariate forecasting using only closing prices, which limits the model's ability to fully understand complex market behavior. Second, some studies utilized limited technical indicators and ignored additional market information such as trading volume and momentum indicators that may contribute significantly to forecasting performance. Third, many existing forecasting models still experience overfitting problems and unstable prediction performance when dealing with highly volatile financial data. Additionally, several studies only evaluated forecasting performance using limited datasets or simple architectures, resulting in moderate generalization capability. Therefore, there remains a need for more robust deep learning models capable of capturing complex temporal relationships while maintaining stable predictive performance across volatile stock market conditions.

The state-of-the-art development in financial time-series forecasting has increasingly shifted toward hybrid and advanced deep learning architectures, including BiLSTM, Attention-based models, and Transformer networks. Among these approaches, BiLSTM has attracted considerable attention because it can process sequential information in both forward and backward directions simultaneously, allowing the model to capture richer contextual dependencies within stock market data. In addition, the integration of technical indicators such as Moving Average (MA) and Relative Strength Index (RSI) has shown potential in improving forecasting accuracy by providing additional information related to market trends and momentum behavior. Several recent studies have reported that combining multivariate input features with BiLSTM architectures can significantly enhance prediction performance compared to conventional LSTM or machine learning models [5]. However, the application of BiLSTM models combined with multiple technical indicators for forecasting Indonesian stock market data remains relatively limited and still requires further investigation.

Based on these research gaps, this study proposes a Bidirectional Long Short-Term Memory (BiLSTM)-based forecasting model for stock price prediction using multivariate financial time-series data. The proposed model incorporates historical stock prices along with several technical indicators, including High, Low, Open, Volume, Moving Average (MA10 and MA20), and Relative Strength Index (RSI), to improve the model's ability in capturing market dynamics and temporal dependencies. The main contribution of this study lies in the implementation of a multivariate BiLSTM architecture combined with adaptive learning optimization techniques to enhance forecasting performance and generalization capability. The performance of the proposed model is evaluated using several regression metrics, namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination ($R^2$). Through this study, it is expected that the proposed approach can provide a more effective and reliable forecasting framework for stock market prediction and contribute to the development of intelligent financial forecasting systems based on deep learning techniques.

## Literature Review

Stock price forecasting has been widely studied due to its importance in financial decision-making and investment analysis. Financial time-series data are characterized by nonlinear, non-stationary, and highly volatile behavior, making accurate forecasting a challenging task. Traditional statistical approaches such as Autoregressive Integrated Moving Average (ARIMA), Support Vector Machine (SVM), and linear regression models have been extensively utilized for stock market prediction tasks. However, these methods generally exhibit limited capability in capturing complex nonlinear relationships and long-term temporal dependencies within financial datasets [6]. As a result, researchers have increasingly shifted toward machine learning and deep learning approaches to improve forecasting accuracy and model robustness.

Deep learning techniques have shown significant potential in financial forecasting because of their ability to automatically extract hidden features from sequential data. Among various deep learning architectures, Recurrent Neural Networks (RNN) have become popular for time-series prediction due to their capability in processing sequential information [7]. Nevertheless, conventional RNN models suffer from the vanishing gradient problem, which limits their ability to learn long-term dependencies in financial time-series data [8]. To address this limitation, Long Short-Term Memory (LSTM) networks were introduced as an improved recurrent architecture capable of storing long-term temporal information using memory cells and gating mechanisms [9]. Several studies have demonstrated that LSTM models outperform traditional statistical and machine learning approaches in stock market forecasting tasks [10].

Recent studies have increasingly explored Bidirectional Long Short-Term Memory (BiLSTM) architectures for financial forecasting applications. Unlike standard LSTM models that process information only in a forward direction, BiLSTM models learn sequential patterns from both past and future contexts simultaneously, allowing richer contextual understanding and improved prediction capability [11]. Previous research reported that BiLSTM-based forecasting models achieved higher prediction accuracy and better generalization performance compared to unidirectional LSTM models in stock market prediction tasks [12]. Furthermore, the integration of dropout regularization and adaptive learning optimization strategies has been shown to improve model stability and reduce overfitting problems during training [13].

In addition to deep learning architectures, the incorporation of technical indicators has become an important aspect of modern stock forecasting research. Technical indicators such as Moving Average (MA), Relative Strength Index (RSI), Bollinger Bands, and Moving Average Convergence Divergence (MACD) are widely used to represent market trends, momentum, and volatility conditions [14]. Several studies have shown that combining historical stock prices with technical indicators significantly improves forecasting performance compared to using closing prices alone [15]. Multivariate forecasting approaches provide additional contextual information that enables deep learning models to better understand market behavior and capture complex price movement patterns [16].

The advancement of state-of-the-art forecasting models has also led to the development of hybrid and attention-based architectures for financial prediction. Convolutional Neural Networks (CNN) combined with LSTM or BiLSTM have been proposed to extract spatial and temporal features simultaneously from stock market data [17]. In addition, Transformer-based architectures and attention mechanisms have recently demonstrated superior performance in capturing long-range dependencies within financial time-series datasets [18]. Despite these advancements, several studies still report challenges related to prediction instability, overfitting, and limited generalization performance when dealing with highly volatile stock market conditions [19]. Moreover, many existing studies focus primarily on global financial markets, while research involving Indonesian stock market datasets remains relatively limited [20].

Based on the reviewed literature, it can be concluded that deep learning approaches, particularly BiLSTM architectures combined with multivariate technical indicators, provide promising capability for stock price forecasting tasks. However, further investigation is still required to improve forecasting robustness, enhance prediction accuracy, and evaluate the effectiveness of advanced architectures in different financial market environments. Therefore, this study proposes a multivariate BiLSTM-based forecasting model using technical indicators to further explore its capability in predicting stock price movements within Indonesian stock market data.

## Method

This study employed a quantitative experimental research methodology to develop and evaluate a deep learning-based forecasting model for stock price prediction using a Bidirectional Long Short-Term Memory (BiLSTM) architecture. The proposed methodology was designed to investigate the capability of deep learning techniques in capturing temporal dependencies and nonlinear patterns within financial time-series data. The overall research procedure consists of several stages, including data collection, data preprocessing, feature engineering, sequence generation, model construction, training and optimization, forecasting, and performance evaluation. The complete workflow of the proposed forecasting framework is illustrated in figure 1.

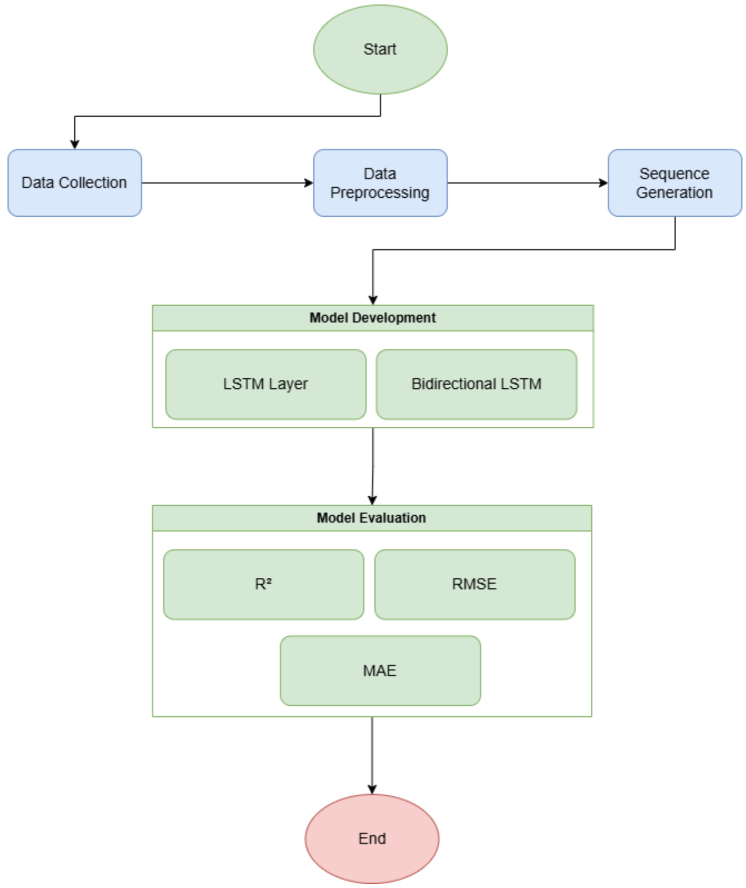


**Figure 1** **Research Framework of the Proposed BiLSTM Forecasting Model**

The research process begins with historical stock market data collection obtained from Yahoo Finance. The collected data then undergo preprocessing stages including data cleaning, handling missing values, data transformation, and normalization. After preprocessing, feature engineering is conducted by generating technical indicators such as Moving Average (MA10 and MA20) and Relative Strength Index (RSI). The processed data are subsequently transformed into sequential time-series input using a sliding window technique before being divided into training and testing datasets. The generated sequences are then used to train the proposed BiLSTM model. Finally, the forecasting performance is evaluated using several regression metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination ($R^2$).

## Data Collection

The dataset used in this study was obtained from Yahoo Finance, which provides publicly accessible historical stock market data. The selected dataset contains daily stock trading information for the chosen stock ticker and includes several attributes such as Date, Open, High, Low, Close, and Volume. These variables represent essential stock market indicators commonly used in financial forecasting analysis. The Close price was selected as the primary target variable because it reflects the final market valuation of the stock at the end of each trading session and is widely used in stock prediction studies.

The collected dataset consists of 239 observations representing sequential daily stock market activities. Since stock price forecasting depends heavily on temporal patterns and sequential relationships, the chronological order of the dataset was maintained throughout the entire experimental process. The historical stock data provide the foundation for training the deep learning model to identify recurring patterns, trends, and price movement behavior within the financial market.

## Data Preprocessing

Data preprocessing is a crucial stage in deep learning-based forecasting because raw financial datasets often contain inconsistencies, missing values, duplicated headers, and incompatible data types. In this study, the preprocessing stage involved several systematic procedures to ensure data quality and suitability for model training. Initially, unnecessary rows generated during the data export process were removed from the dataset. The dataset originally contained duplicate header information such as “Ticker” and several invalid rows that could interfere with the preprocessing pipeline. After the cleaning process, the dataset columns were restructured into five primary attributes: Date, Close, High, Low, Open, and Volume. Furthermore, the Date column was converted into datetime format to preserve the chronological order of stock transactions and facilitate time-series analysis. Numerical attributes, including Close, High, Low, Open, and Volume, were transformed into floating-point numeric formats to ensure compatibility with mathematical computations and deep learning model processing. These preprocessing steps were essential to produce a clean, consistent, and structured dataset suitable for training the forecasting models.

After data cleaning, normalization was performed using the MinMaxScaler technique from Scikit-learn. Normalization transforms all feature values into the range between 0 and 1 using the following equation:

(1)

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

$X$ *represents the original feature value,*

$X_{min}$ *is the minimum value of the feature,*

$X_{max}$ *is the maximum value of the feature.*

Normalization is important because stock market variables often have significantly different scales, particularly trading volume compared to stock prices. Without normalization, features with larger numerical ranges may dominate the optimization process and negatively affect model convergence.

## Feature Engineering

Feature engineering was conducted to enhance the model’s capability in capturing market dynamics and improving forecasting accuracy. In addition to the original stock attributes, several technical indicators were generated and incorporated into the dataset as additional predictive features. The technical indicators used in this study include the Moving Average over 10 periods (MA10), Moving Average over 20 periods (MA20), and Relative Strength Index (RSI). These indicators were selected to provide information related to market trends, momentum, and price movements, thereby improving the model's ability to identify patterns within the stock market data.

The Moving Average indicators were used to represent short-term and medium-term market trends by smoothing stock price fluctuations over a specified time window. The Moving Average formula is defined as follows:

$$\mathrm{MA} = \frac{1}{n}\sum_{i=1}^{n} P_i \tag{1}$$

$P_i$ $represents\ stock\ prices,$

$n$ $denotes\ the\ observation\ period.$

Meanwhile, the Relative Strength Index (RSI) was used to measure market momentum and identify overbought or oversold conditions. The RSI formula is defined as:

$$RSI = 100 - \frac{100}{1 + RS} \tag{2}$$

$RS$ represents the ratio between average gain and average loss.

### Sequence Generation

Because stock market data are sequential time-series data, the dataset must be transformed into supervised learning sequences before being processed by the BiLSTM model. In this study, a sliding window technique was applied to generate sequential input-output pairs.

Each input sequence consisted of 20 previous time steps containing 8 features, while the output represented the next predicted stock closing price. This approach enables the model to learn temporal dependencies and historical market behavior over a fixed observation window.

Mathematically, the sequence generation process can be represented as:

$$Xt = [xt - 20, xt - 19, \ldots, xt - 1] \rightarrow yt \tag{3}$$

After sequence generation, the dataset was divided into training and testing sets using an 80:20 ratio. The resulting dataset dimensions were:

Training data: (156, 20, 8)

Testing data: (24, 20, 8)

### Proposed BiLSTM Architecture

This study proposes a Bidirectional Long Short-Term Memory (BiLSTM)-based forecasting architecture. BiLSTM is an extension of the traditional LSTM network that processes sequential information in both forward and backward directions simultaneously, enabling the model to capture richer contextual dependencies within time-series data. The proposed architecture consists of several deep learning layers designed to improve forecasting performance. The first layer is a Bidirectional LSTM layer with 64 hidden units, which is responsible for learning temporal patterns from both past and future sequences. This layer is followed by a Dropout layer that serves as a regularization mechanism to reduce overfitting by randomly deactivating neurons during the training process. Subsequently, an additional LSTM layer with 32 hidden units is employed to further refine the extracted temporal features. The learned representations are then passed into a Dense layer with 32 neurons to perform nonlinear feature transformation before reaching the final output layer. The output layer consists of a single dense neuron that generates the predicted stock price value. Furthermore, the Adam optimizer was selected because of its adaptive learning capability and efficient convergence performance in deep learning optimization tasks, making it suitable for financial time-series forecasting applications.

### Model Training and Optimization

The model training process was conducted using the Mean Squared Error (MSE) loss function because MSE is widely used for regression and forecasting problems. The MSE formulation is defined as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4}$$

$y_i$ *represents actual stock prices,*

$\hat{y}_i$ *represents predicted stock prices,*

$n$ *denotes the total number of observations.*

The model was trained for 100 epochs using batch-based learning. During training, validation data were used to monitor generalization performance and detect potential overfitting behavior. Additionally, the ReduceLROnPlateau callback was implemented to dynamically reduce the learning rate whenever validation loss stagnated for several epochs.

G. Performance Evaluation

The performance of the proposed forecasting model was evaluated using three regression evaluation metrics:

Mean Absolute Error (MAE)

Root Mean Square Error (RMSE)

Coefficient of Determination ($R^2$)

The MAE formula is defined as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{5}$$

The RMSE formula is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

The coefficient of determination is calculated using:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \tag{7}$$

$y_i$ *represents actual stock prices,*

$\hat{y}_i$ *represents predicted stock prices,*

$\bar{y}$ *represents the average actual stock price.*

These metrics provide comprehensive evaluation of prediction accuracy, forecasting stability, and the model's ability to explain stock price variability.

## Result

The proposed Bidirectional Long Short-Term Memory (BiLSTM) forecasting model was developed using multivariate stock market data containing historical stock prices and several technical indicators, including High, Low, Open, Volume, Moving Average over 10 and 20 periods (MA10 and MA20), and Relative Strength Index (RSI). These indicators were incorporated to provide the model with richer contextual information regarding market trends, momentum, and price volatility. Prior to model training, the dataset underwent several preprocessing stages, including data cleaning, normalization using the MinMaxScaler technique, and feature engineering to generate additional technical indicators. The time-series data were then transformed into sequential input structures using a sliding window approach with 20 previous observations as input sequences. As a result, the final dataset was divided into training data with dimensions of (156, 20, 8) and testing data with dimensions of (24, 20, 8). The proposed architecture consisted of a Bidirectional LSTM layer capable of learning information from both forward and backward temporal directions, followed by an additional LSTM layer to further extract sequential dependencies from historical stock price movements. To reduce the risk of overfitting, dropout regularization layers were added between hidden layers, while fully connected dense layers were utilized to generate the final forecasting output.

The model training process demonstrated stable and effective convergence throughout the training epochs. As illustrated in figure 2, both the training loss and validation loss showed a consistent downward trend, indicating that the model successfully learned the underlying temporal patterns and relationships within the stock market dataset. During the initial epochs, the training loss decreased significantly from approximately 0.035 to below 0.010, showing rapid adaptation of the model to the data distribution. Simultaneously, the validation loss also decreased steadily and remained relatively low compared to the training loss, eventually approaching values near 0.001. This behavior suggests that the model achieved good generalization capability without experiencing severe overfitting problems. In several epochs, slight fluctuations in validation loss were observed due to the highly volatile nature of financial time-series data;

however, the overall trend remained stable. Moreover, the implementation of the ReduceLROnPlateau callback contributed significantly to the optimization process by automatically reducing the learning rate whenever the validation performance stagnated. This adaptive learning strategy allowed the model to achieve more stable convergence and prevented the optimization process from becoming trapped in local minima during training.

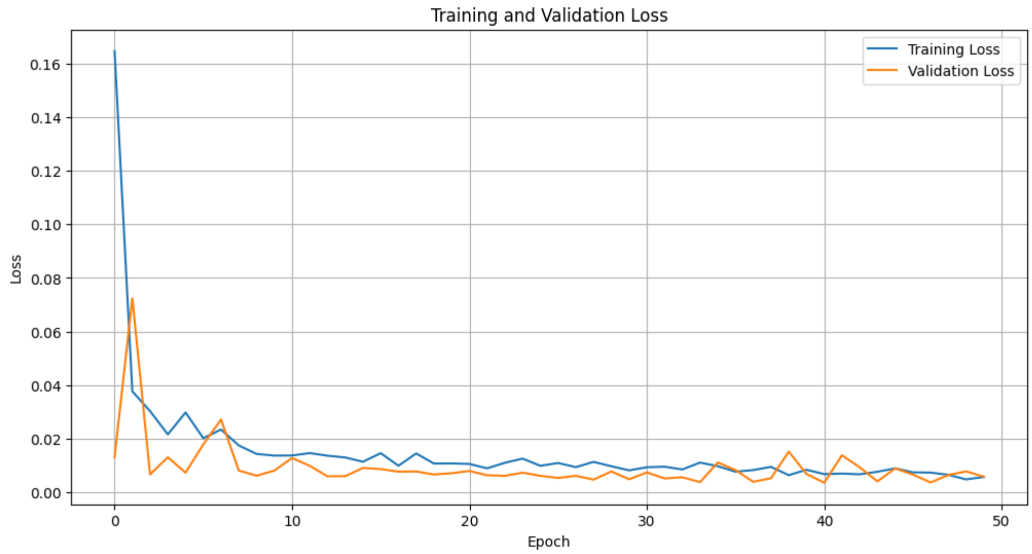


**Figure 2 Training and Validation Loss of the Proposed BiLSTM Model**

To evaluate the forecasting performance of the proposed BiLSTM model, several commonly used regression evaluation metrics were employed, namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination ($R^2$). These metrics were selected because they provide comprehensive insights into the prediction accuracy and generalization capability of the forecasting model. MAE measures the average absolute difference between the actual stock prices and the predicted values, providing a straightforward interpretation of the average forecasting error. RMSE was utilized to measure the magnitude of prediction errors while giving higher penalties to larger deviations, making it particularly suitable for financial forecasting tasks where sudden price fluctuations may occur. In addition, the $R^2$ score was used to evaluate how well the proposed model could explain the variance within the stock price data. The evaluation process was conducted using unseen testing data to ensure that the reported performance reflected the model's actual predictive capability rather than memorization of training patterns.

The evaluation results presented in table 1 demonstrate that the proposed forecasting model achieved moderate predictive performance on the stock market dataset. The model obtained an MAE value of 15.5805, indicating that the average prediction error between the actual and predicted stock prices remained relatively acceptable considering the volatility of stock market movements. Furthermore, the RMSE value of 21.0883 suggests that although several prediction deviations still occurred, the overall forecasting error was reasonably controlled. The obtained $R^2$ score of 0.4954 indicates that approximately 49.54% of the variability in stock price movements could be explained by the proposed BiLSTM model. Although the $R^2$ value has not yet reached a highly optimal level, the results confirm that the model was capable of capturing important temporal relationships and underlying trends from historical stock price data. These findings indicate that the integration of technical indicators and deep learning architecture contributed positively to forecasting performance, while also highlighting the inherent complexity and stochastic behavior of financial time-series prediction tasks.

**Table 1** **Performance Evaluation of the Proposed Forecasting Model**

| Metric | Value |
|---|---|
| MAE | 15.5805 |
| RMSE | 21.0883 |
| $R^2$ Score | 0.4954 |

The experimental results demonstrate that the proposed BiLSTM forecasting model achieved moderate predictive performance in forecasting stock price movements. Based on the evaluation metrics presented in Table 1, the model produced an MAE value of 15.5805, indicating that the average absolute difference between the predicted values and the actual stock prices remained relatively manageable. This result suggests that the proposed model was capable of generating predictions that were reasonably close to the actual market prices despite the highly volatile nature of stock market data. Furthermore, the RMSE value of 21.0883 indicates that several prediction errors with larger deviations were still present during the forecasting process. Since RMSE penalizes larger errors more heavily than MAE, the obtained result implies that the model occasionally struggled to accurately predict sudden and extreme price movements. Nevertheless, considering the nonlinear and stochastic characteristics of financial time-series data, the achieved RMSE value still reflects acceptable forecasting capability. In addition, the obtained $R^2$ score of 0.4954 indicates that approximately 49.54% of the variance in stock price movements could be explained by the proposed model. Although the $R^2$ value has not yet reached a highly optimal level, the result confirms that the BiLSTM architecture successfully captured important temporal dependencies and sequential patterns embedded within historical stock market data.

Figure 3 presents the comparison between actual stock prices and predicted prices generated by the proposed forecasting model. The visualization shows that the predicted price curve generally follows the overall trend and directional movements of the actual stock prices, particularly during gradual upward and downward market trends. This indicates that the BiLSTM model was effective in learning long-term dependencies and temporal relationships within the time-series dataset. However, several discrepancies between actual and predicted values can still be observed, especially during periods characterized by sharp price fluctuations and sudden market volatility. In these situations, the prediction curve tends to appear smoother compared to the actual stock price movements. This phenomenon commonly occurs in deep learning-based forecasting models because neural networks are optimized to minimize overall prediction error across the entire dataset, causing the model to generate more stable and generalized predictions rather than highly reactive responses to abrupt price changes. Additionally, the limited dataset size and the absence of external influencing factors, such as macroeconomic variables, market sentiment, or financial news, may also contribute to the remaining prediction inaccuracies. Despite these limitations, the forecasting results demonstrate that the proposed

BiLSTM model possesses promising capability for capturing the underlying dynamics of stock price behavior and can serve as a strong baseline model for future financial forecasting research.

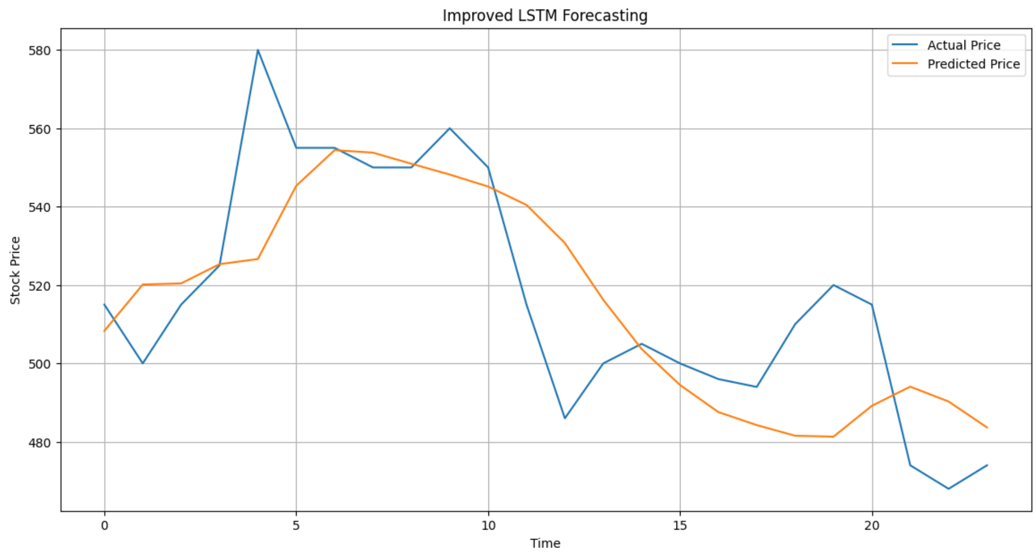


**Figure 3 Comparison Between Actual and Predicted Stock Prices**

Overall, the obtained results indicate that the proposed BiLSTM-based forecasting model provides promising capability for stock price prediction tasks. The integration of multiple technical indicators contributed to improving the model's ability to learn complex market dynamics and temporal relationships within the dataset. Nevertheless, the moderate $R^2$ value suggests that stock market forecasting remains highly challenging due to the nonlinear and stochastic characteristics of financial time-series data. Future research may improve forecasting performance by incorporating external factors such as macroeconomic indicators, sentiment analysis from financial news, or hybrid deep learning architectures to better capture complex market behavior.

## Discussion

The results of this study demonstrate that the proposed Bidirectional Long Short-Term Memory (BiLSTM) model was capable of learning temporal patterns from historical stock market data and generating relatively stable forecasting performance. The integration of multiple technical indicators, including Moving Average (MA10 and MA20), Relative Strength Index (RSI), High, Low, Open, and Volume, contributed positively to the model's ability to capture both trend information and momentum behavior in stock price movements [21]. Compared to conventional statistical forecasting approaches, deep learning models such as BiLSTM offer superior capability in modeling nonlinear relationships and sequential dependencies within financial time-series data [22]. The obtained training and validation loss curves indicate that the model successfully converged during training and maintained good generalization capability without severe overfitting. This finding suggests that the proposed architecture effectively balanced model complexity and regularization through the implementation of dropout layers and adaptive learning rate reduction.

Despite achieving promising results, the evaluation metrics indicate that stock price forecasting remains a highly challenging task. The obtained $R^2$ score of 0.4954 shows that although the model was able to explain approximately half of the variance in stock price movements, a substantial portion of market behavior remained unpredictable. This limitation is primarily caused by the highly volatile and stochastic nature of stock market data, where price movements are influenced not only by historical patterns but also by numerous external factors such as macroeconomic conditions, investor sentiment, government policies, global financial events, and unexpected market news [23]. Furthermore, the relatively small dataset used in this study may have limited the model's ability to learn broader market dynamics and more diverse temporal patterns. In periods of sharp market fluctuations, the prediction results tended to become smoother than the actual stock prices, indicating that the model prioritized minimizing overall prediction error rather than accurately capturing extreme volatility. This behavior is common in recurrent neural network-based forecasting models, particularly when dealing with noisy financial datasets.

Another important finding from this study is the effectiveness of Bidirectional LSTM in capturing sequential dependencies from both forward and backward directions. Unlike standard LSTM models that process information only in one temporal direction, the BiLSTM architecture allows the network to utilize contextual information from past and future sequences simultaneously during training. This capability enhances the model's understanding of temporal structures within stock market data and improves prediction stability [24]. The decreasing validation loss throughout the training process further confirms that the model successfully extracted meaningful features from the multivariate input data. In addition, the implementation of the ReduceLROnPlateau callback contributed significantly to optimization stability by dynamically adjusting the learning rate when validation performance stagnated. This adaptive mechanism helped the model avoid unstable convergence and improved the overall training efficiency.

Although the proposed model demonstrated moderate forecasting performance, several improvements can still be explored in future research to achieve higher prediction accuracy. One possible enhancement is the incorporation of additional external variables, such as macroeconomic indicators, inflation rates, exchange rates, commodity prices, or sentiment analysis derived from financial news and social media platforms. These external factors may provide richer contextual information that cannot be fully represented by historical stock prices alone. Furthermore, future studies may investigate hybrid deep learning architectures, such as CNN-BiLSTM, Attention-based LSTM, Transformer models, or ensemble learning approaches, which have shown promising performance in recent financial forecasting research [25]. Increasing the dataset size and applying more advanced validation strategies, such as walk-forward validation, may also improve model robustness and generalization performance. Therefore, while the proposed BiLSTM model provides a solid foundation for stock price forecasting, continuous refinement and integration of more sophisticated techniques remain essential for handling the complexity of real-world financial markets.

## Conclusion

This study successfully developed and evaluated a Bidirectional Long Short-Term Memory (BiLSTM)-based forecasting model for predicting stock price movements using multivariate financial time-series data. The proposed model utilized historical stock prices combined with several technical indicators, including High, Low, Open, Volume, Moving Average (MA10 and MA20), and Relative Strength Index (RSI), to enhance the model's capability in capturing complex temporal relationships and market dynamics. The experimental results demonstrated that the BiLSTM architecture was capable of learning underlying patterns within stock market data and generating relatively stable forecasting performance, as reflected by the obtained evaluation metrics of MAE = 15.5805, RMSE = 21.0883, and $R^2$ = 0.4954. Furthermore, the visualization results indicated that the predicted stock prices generally followed the overall trend and direction of the actual stock prices, particularly during gradual market movements, although deviations still occurred during periods of high volatility. The implementation of technical indicators, dropout regularization, and adaptive learning rate optimization contributed positively to improving model convergence and generalization capability during training. Nevertheless, the results also revealed that stock market forecasting remains highly challenging due to the nonlinear, volatile, and stochastic characteristics of financial markets, where historical price information alone is often insufficient to fully explain future market behavior. Therefore, future research is recommended to incorporate additional external variables such as macroeconomic indicators, financial news sentiment, and hybrid deep learning architectures, including Attention mechanisms or Transformer-based models, to further improve forecasting accuracy and robustness. Overall, the proposed BiLSTM model provides a promising and effective approach for stock price forecasting and demonstrates the potential application of deep learning techniques in intelligent financial market analysis systems.

## Declarations

### Author Contributions

Conceptualization: E.G.G.; Methodology: E.G.G.; Software: E.G.G.; Validation: E.G.G.; Formal Analysis: E.G.G.; Investigation: E.G.G.; Resources: E.G.G.; Data Curation: E.G.G.; Writing – Original Draft Preparation: E.G.G.; Writing – Review and Editing: E.G.G.; Visualization: E.G.G.; All authors have read and agreed to the published version of the manuscript.

### Data Availability Statement

The data presented in this study are available on request from the corresponding author.

### Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

### Institutional Review Board Statement

Not applicable.

### Informed Consent Statement

Not applicable.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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