JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

# Bidirectional LSTM-Based Deep Learning Model for Stock Market Prediction

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**Abstract**

Stock market prediction remains a challenging task due to the highly volatile, nonlinear, and non-stationary nature of financial time-series data. Accurate forecasting of stock prices is essential for investors, financial institutions, and policymakers to minimize risk and optimize returns. This paper proposes a deep learning-based Bidirectional Long Short-Term Memory (Bi-LSTM) model for predicting stock price trends. The proposed approach is evaluated using historical Google stock data spanning from 2004 to 2022, obtained from Kaggle. Extensive data preprocessing is applied to improve data quality, followed by feature selection and an 80:20 training–testing split. Experimental results demonstrate that the proposed Bi-LSTM model significantly outperforms the conventional LSTM model, achieving an MSE of 72.777 and RMSE of 45.328, compared to 5296.6212 and 2054.7156, respectively, for the traditional LSTM. The findings confirm that Bi-LSTM effectively captures complex temporal dependencies in stock price data, providing a robust and scalable solution for stock market forecasting.

**Keywords:** Stock Market Prediction, Deep Learning, Bi-LSTM, Time Series Forecasting, Financial Data Analysis

## 1. Introduction

The stock market plays a crucial role in the global economy by facilitating capital generation and investment opportunities. Stock prices, however, are highly volatile and influenced by numerous factors such as economic indicators, political events, investor sentiment, and company performance. This complexity makes accurate stock market prediction a challenging task.

Traditional prediction approaches, including fundamental and technical analysis, rely heavily on predefined indicators and expert-defined rules. While effective to some extent, these methods struggle to capture nonlinear dependencies and long-term temporal relationships present in financial time-series data. Machine learning (ML) models such as Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN) have been widely explored, but their performance often degrades when handling large-scale, noisy, and non-stationary datasets.

Recent advancements in deep learning (DL), particularly Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, have shown promising results in time-series forecasting tasks. LSTM networks address the vanishing gradient problem and can learn long-term dependencies in sequential data. However, standard LSTM processes data only in a forward direction, limiting its contextual understanding.

To overcome this limitation, this paper proposes a Bidirectional LSTM (Bi-LSTM) model that captures both past and future contextual information, thereby improving prediction accuracy for stock price trends.

## 2. **Motivation and Contribution**

The motivation stemmed from the inherent complexity and volatility of financial markets, where stock prices can fluctuate drastically within fractions of a second, posing challenges even for the most experienced traders. The competitive nature of the stock market has driven a persistent quest for accurate and timely prediction methods, as the ability to foresee stock price trends can lead to significant financial gains, while failure can result in substantial losses. Traditional methods, although effective to some extent, have often fallen short in capturing the intricate, non-linear dependencies and the massive influx of real-time data influencing stock prices. This has necessitated the exploration of advanced computational approaches, particularly Deep Learning (DL), which have shown immense potential in addressing these challenges.

In this work, an effective and precise SMP approach will be proposed in which an advanced DL based Bi-LSTM classifier is used for predicting stock price trends on Google stock dataset. Bi-LSTM, which is basically an advanced variant of RNN, is uniquely equipped to process sequential data by considering both past and future contexts in time-series data, making it highly suitable for modelling stock price trends. By leveraging the inherent capabilities of Bi-LSTM to capture complex temporal patterns, this research aims to enhance prediction accuracy and provide a robust framework for understanding stock price movements. My contribution lies in designing and implementing this Bi-LSTM-based prediction model, rigorously evaluating its performance, and showcasing its advantages over conventional methods. This work highlights importance of DL in financial forecasting while highlighting how advanced models like Bi-LSTM can be instrumental in developing predictive systems which can easily be adopted and implemented in current dynamic financial markets.

## 3. Literature Review

- **Zhu, Tianlei et al. [26],** Owners must be able to foresee stock changes because the stock market is vital to the whole industry. This problem could be greatly alleviated by an efficient forecasting system. The authors of this paper used google Inc. in which 3810 closing price stocks were taken. Later on for classification approach, LSTM have been used for predicting future value of stocks. They developed 3-layered LSTM model which divided whole database into 8:2 ratio of training and testing. The findings showed that while the LSTM approach performed well in predicting the overall trend of Google Inc.'s value, however, it had trouble making highly accurate predictions about the precise price.
- **M. Usmani, et al. [27],** aimed to predict values of KSE (Karachi Stock Exchange) during closing day by utilizing different ML approaches. Moreover, they also analysed different parameters related to stock price including price of oil, gold & silver, current interest rate, value of Foreign exchange and social networking sites with trending news for predicting the positive or negative value of the stock. Before utilizing the new ML techniques they decided to include previous statistical

approaches including SMA and ARIMA in their work also. Then, they used their 4 ML classifiers (SVM, SLP, RBF and MLP) to compare their performance with traditional statistical models. Through simulating results they revealed MLP serving as best performance model with oil price being the best attribute for predicting market trend.

- **Reddy, V. Kranthi Sai, et al. [28],** in the financial sector, stock trading stands as one of the most vital activities. Predicting trend of stock values or other trades on exchanges is a critical endeavor known as SMP. The researchers of this study delves into SMP utilizing ML techniques. Typically, stockbrokers either use technical or fundamental or time series analysis for making predictions. Here, authors employed Python as the programming language for implementing SVM for forecasting stock market trends. Later they employed ML approach that were trained on historically available stock data for learning patterns and making precise predictions. This SVM was implemented on 3 different marketers for forecasting their large and small capital by using daily and minute pricing.
- **Mehtab, Sidra, et al. [29],** forecasting future stock price movements has consistently posed a significant challenge for researchers. Proponents of the efficient market hypothesis (EMH) argue that creating a predictive framework with the capability to accurately forecast stock price fluctuations is unattainable. However, numerous pivotal studies in the literature have shown that stock price time series can be predicted with considerable accuracy, offering a counterpoint to the EMH perspective. Considering this finding, the authors of this paper developed a forecasting model using not only statistical and ML techniques but also using DL methods. The data used by them was gathered at an interval of 5 minutes of a well-known and reputed Indian company i.e., NSE. This data was aggregated in 3 slots during day and later used same data for making predictions.
- **Vijh, Mehar, et al. [30],** Authors employed ANN and RF methods to forecast the closing prices for next day across five companies from various sectors. They leveraged 4 key financial metrics (Open, High, Low, and Close prices) for generating new variables which served as input parameters to predictive models. Moreover, they showcased the superiority of their model on standard evaluation metrics i.e., RMSE and MAPE. Such indices' consequently declining values imply that the models were quite good at forecasting stock closing values.
- **I. Parmar *et al*., [31],** SMP basic responsibility is to predict future financial value of stocks. A growing trend in this field is implementation of AI based ML methods, which predict stock prices by analysing current market indices and training on historical data. Machine learning incorporates various methods for improving the preciseness and reliability of predictions. This study emphasized on using Regression and LSTM models for stock prices, taking into account key factors like open and close, high, lows, and trading volume.
- **Kohli, P.P.S, et al. [32],** Stock market systems are inherently complex, often surpassing the predictive capabilities of any individual. However, accurately forecasting stock prices is essential for investors aiming to secure significant profits. This project focuses on predicting the patterns of the Bombay Stock Exchange (BSE) by considering influential factors of commodity prices, historical

values, and FEX. These factors were utilized by providing an input to ML models. The performance of these models was evaluated and compared against established benchmarks. A structured relationship among the attributes was identified, revealing that gold prices had the strongest positive correlation with market performance. Among the techniques tested, the AdaBoost algorithm emerged as the most effective.

## 4. Problem Formulation

Stock market prediction systems must handle high volatility, nonlinear patterns, and rapidly changing market conditions. Most existing ML-based approaches rely heavily on historical data and struggle with non-stationarity and sudden market shifts. Moreover, unidirectional models fail to fully exploit temporal dependencies.

The objective of this research is to design a robust deep learning-based model that:

- Effectively captures complex temporal dependencies,
- Reduces prediction error,
- Adapts to large-scale financial time-series data.

## 5. Methodology

Since, a systematic approach is followed by the proposed Bi-LSTM SMP method starting from gathering data from kaggle.com to making final predictions using BI-LSTM. The brief but step by step working of model is explained in this section (see Figure 4)

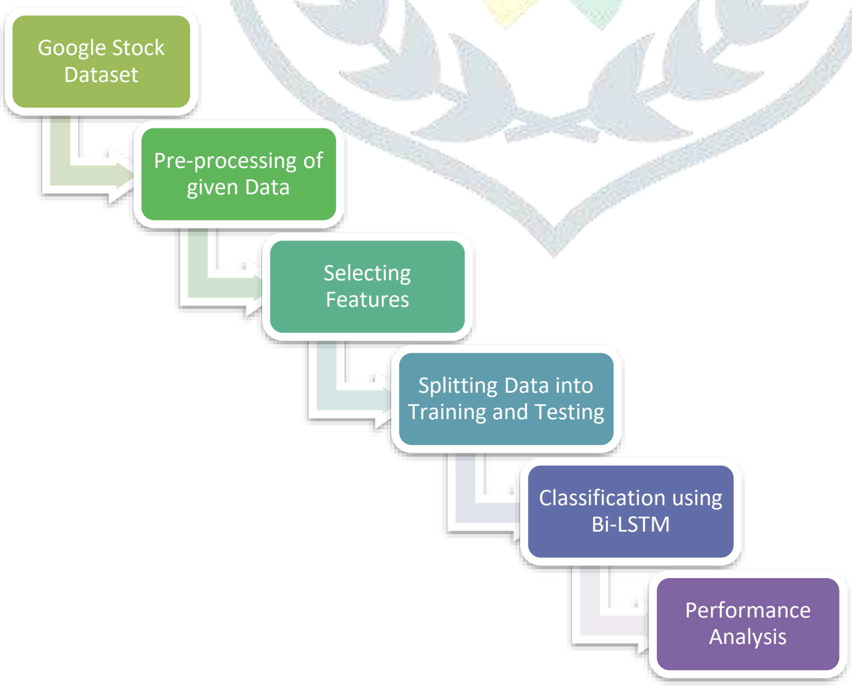


Figure 4. Working Flow of proposed BI-LSTM based SMP model

- **Dataset Acquisition:** here, Google stock dataset [51], sourced from Kaggle.com, is used as this dataset is comprehensive, and encompassing essential financial indicators across seven key columns: date, open, high, low, close, adjusted close, and volume. Each column provides critical insights into the stock's performance, capturing its daily fluctuations and trading volumes. The dataset spans an extensive period from 2004 to 2022, offering a rich historical view that aids in recognizing long-term trends and patterns in Google's stock performance.
- **Pre-Processing Data:** Soon after collecting the necessary data, pre-processing stage is initiated for refining and formatting dataset to make them more informative and useful. During this phase, dataset is meticulously examined for any null values and empty columns, which are then appropriately handled using mean imputation method and deletion (if column has missing value over 80%) to avoid introducing bias or errors into the model. Additionally, label encoding method is implemented for converting any categorical data into numerical data to maintain uniformity across the dataset.
- **Selecting Features:** After processing dataset, the focus shifts to selecting relevant attributes that relate most with the prediction. As dataset contains multiple columns such as market opening and closing statistics, the analysis prioritizes the closing market data in relation to specific dates. Closing value is often considered a critical indicator as it reflects the net effect of all trading activities, including market trends, investor reactions, and economic news, occurring throughout the day. This targeted approach simplifies the dataset as well as enhances the model's ability to detect meaningful patterns, leading to more accurate and reliable predictions while reducing data redundancy.
- **Data Splitting:** In the subsequent step, the selected data is split into training and testing subsets using an 80:20 ratio. This means that 80% of the dataset is utilized for training the model, enabling it to understand trends and relationships from the historical stock data. The remaining 20% is reserved for testing, which is crucial for evaluating the model's performance and ensuring its predictive accuracy. This division helps in preventing overfitting and ensures improves generalizability of Bi-LSTM to new, unseen data, thereby providing reliable and accurate stock predictions.
- **Bi-LSTM Initialization:** Next, proposed Bi-LSTM model is initialized wherein different important parameters like learning rate, layers etc., is defined as shown in Table 4.

**Table 4.** Configuration setup for Bi-LSTM based prediction model

| Parameters | Values |
|---|---|
| Bi-LSTM Layers | 4 |
| Bi-LSTM Units | 200 |
| Dropout Factor | 0.3 |
| Dense O/P Layer | 1 |

| | |
|---|---|
| Activation | Linear |
| Optimizer | Adam with 0.001 learning rate |
| Loss Model | Mean Square Error |
| Epochs | 30 |
| Batch Size | 16 |
| Verbose | 2 |

- **Classification using Bi-LSTM:** once the model is initialized, training data is passed to it, so that it can learn patterns from given data. The model extracts important patterns and gets trained and then 20% of unseen data is passed to it for checking its efficiency. The results obtained are simulated in next chapter of this thesis to comprehend the supremacy of proposed approach for predicting stock values.

## 6. Results and Discussions

Here, we have examined the performance of proposed Bi-LSTM based SMP approach on google stocks. The simulations were conducted in Python Software, utilizing a system equipped with an Intel i3 core processor, 8GB of RAM, and a 1TB HDD to ensure smooth execution of the simulation software. The supremacy of Bi-LSTM is demonstrated by comparing its performance against the traditional LSTM model, focusing on key metrics such as error values. This comparative analysis highlights the superiority of the Bi-LSTM model in capturing complex stock market patterns, resulting in more accurate predictions and lower error rates.

### 5.1 Performance Evaluation

In the beginning of the simulations, we have observed the training loss curves attained by conventional LSTM and proposed Bi-LSTM model, see Figure 5.1 and Figure 5.2 respectively. This training loss provides valuable insights of both models during their learning process.

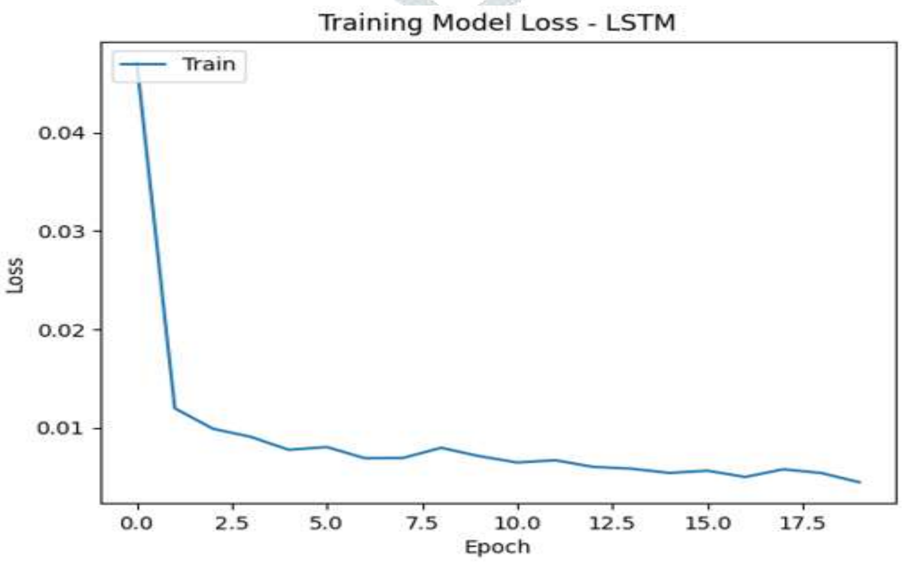


Figure 5.1. Training Loss curve obtained for traditional LSTM


Figure 5.2. Training Loss curve obtained for proposed Bi-LSTM

As seen from the given graph, we observed that LSTM model may take longer to converge due to its unidirectional learning approach, which limits its calibre to devise patterns from given data. In contrary, the Bi-LSTM has bidirectional architecture, demonstrates a more stable and faster convergence. The loss curve of the Bi-LSTM shows a steeper decline in training loss, reflecting its enhanced ability to model complex temporal dependencies by considering bidirectional data, making it faster and more efficient learning, and hence a more effective tool for SMP compared to traditional LSTM model.

In next phase, we have also examined some basic metrics of proposed model while analyzing its performance attributes. During this simulating behavior, parameters like “Acc”, “P”, “R” and “F1” are calculated. As demonstrated in Figure 5.3, the “ACC” of proposed Bi-LSTM model was found to be a remarkable 96%, indicating a high level of correct predictions across the dataset. The proportion of positive predictions that were truly correct, was found to be P=100%, showcasing the model's ability to make highly accurate predictions when it classifies a trend as positive. On the other hand, the “R”, which represents the model's ability to identify all relevant positive instances, was observed to be around 43.2%, suggesting that while the model is precise, there is room for improvement in capturing all positive instances. Finally, the “F1” stood at 60.3%, providing an overall evaluation of the model's performance in terms of both identifying and correctly classifying stock trends. Also, the precise values of these parameters are depicted in Table 5.1.

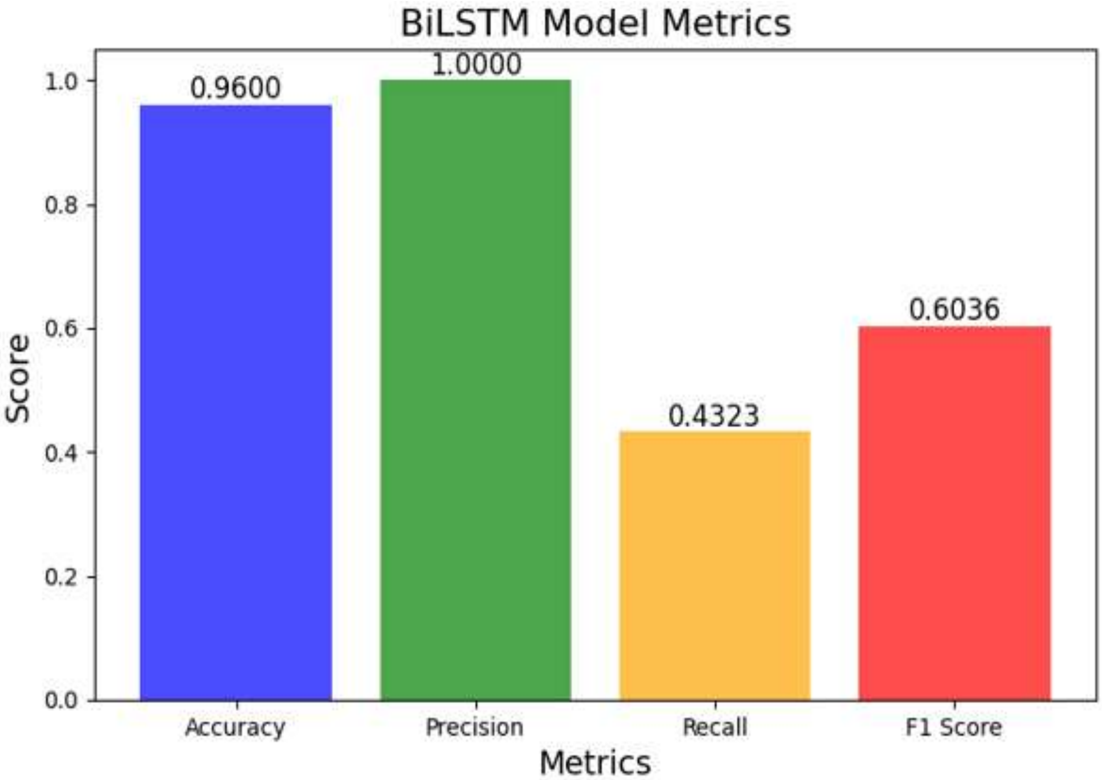


Figure 5.3. Performance Analysis of proposed Bi-LSTM model

**Table 5.1.** Value of Basic parameters for Proposed Bi-LSTM

| **Metrics** | **Values** |
|---|---|
| ACC | 96% |
| Precision | 100% |
| Recall | 43.23% |
| F1-Score | 60.36% |

Additionally, to prove the efficiency of proposed method over traditional LSTM method, we compared their performance with actual stock price on given google stocks. The comparative results are showcased in Figure 5.4 with x-axis depicting time period and y-axis depicting value of stock respectively.

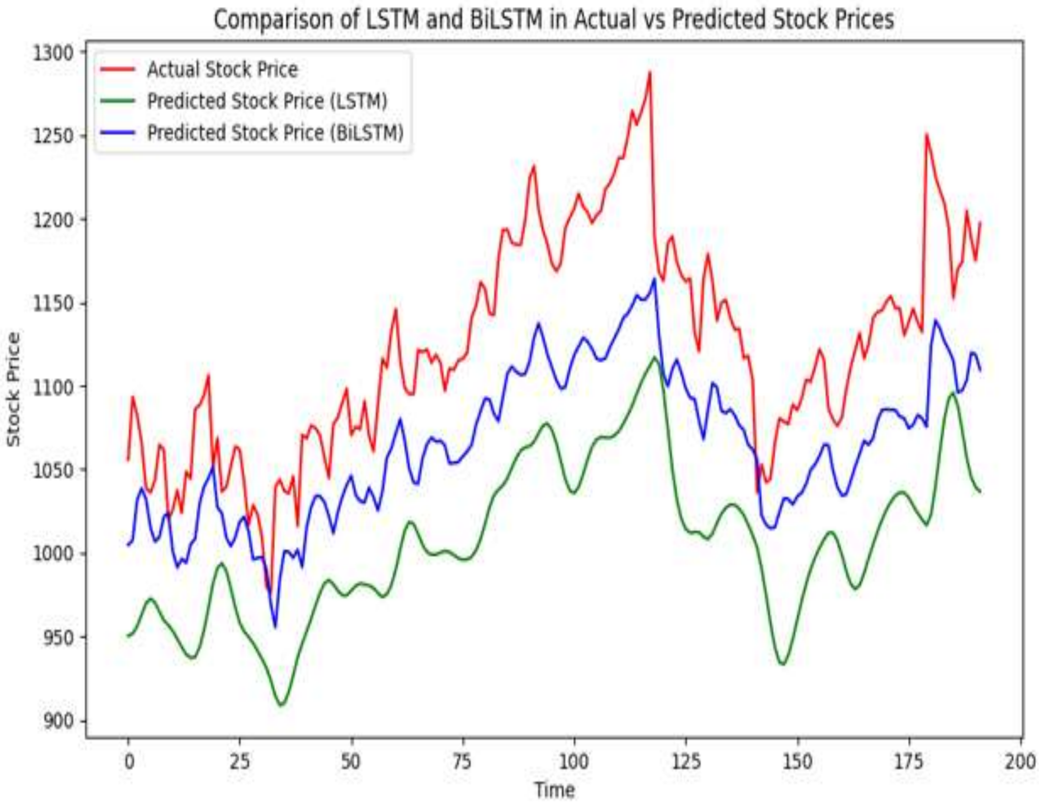


Figure 5.4. Comparative Analysis of Trends observed in different models

The analysis of the given graphs reveals a distinct contrast between actual stock prices and predicted trends obtained in traditional LSTM and the proposed Bi-LSTM models. The actual stock price trajectory begins around a value of 1050, exhibiting fluctuations over time, and ultimately concludes at approximately 1200. When evaluating traditional LSTM model, it is evident that the predicted trend starts significantly lower at around 950, resulting in a considerable error gap between predicted and actual trend. This disparity continues, with the LSTM predictions ending below 1050, reflecting a notable degradation in performance and accuracy. Conversely, the proposed Bi-LSTM model demonstrates a much closer alignment with the actual stock price trends. The Bi-LSTM's predicted trend initiates above 1000, showing a more accurate starting point and a closer approximation to the actual stock values throughout the observed period. The trend predicted by the Bi-LSTM model fluctuates in a manner consistent with the actual stock prices and concludes near 1100, substantially reducing the error margin when compared to the traditional LSTM model. The superior performance of the Bi-LSTM model is further corroborated by the metrics presented in Table 5.2, where the MSE and RMSE values clearly indicated Bi-LSTM’s efficiency with significantly lower error rates than the LSTM model.

**Table 5.2.** Error values observed in LSTM and Bi-LSTM

| Metrics | Traditional LSTM | Proposed Bi-LSTM |
|---|---|---|
| **MSE** | 5296.6212 | 72.777 |
| **RMSE** | 2054.7156 | 45.328 |

The MSE for the Traditional LSTM model is notably high at 5296.6212, indicating a huge error in identifying future trends. In contrast, the Proposed Bi-LSTM model achieves a remarkably lower MSE of 72.777, demonstrating its superior capability in minimizing prediction errors. Similarly, RMSE values further highlight the improved working of proposed Bi-LSTM model, as it was recorded at 2054.7156 for standard LSTM, whereas the Bi-LSTM model significantly reduces this error metric to 45.328. This drastic reduction in RMSE underscores the Bi-LSTM model's enhanced precision in forecasting stock prices, providing a more reliable and accurate tool for stock market predictions. These metrics collectively affirm the efficacy of proposed Bi-LSTM model in outperforming the traditional LSTM in terms of "ACC" and error minimization.

## 6. Conclusion and Future Scope

In conclusion, this research highlights the development and implementation of a Bi-LSTM-based approach for SMP on Google stock data. In order to overcome the shortcomings of conventional LSTM designs, especially with regard to identifying the intricate structures and relationships over time present in market data, the proposed Bi-LSTM model was painstakingly created. Through a comprehensive simulation using Python, the Bi-LSTM model demonstrated superior performance in predicting stock price trends, as evidenced by significantly lower error metrics, including MSE and RMSE, compared to the traditional LSTM model. The analysis of key performance metrics like ACC=96%, (P=100%) to showcase its capability to predict stock market trends with high reliability. Despite a recall value of 43.2% and an F1-score of 60.3%, which suggest room for further improvement, the overall performance metrics indicate a substantial advancement over traditional models. The graphical representation of stock price trends corroborates these findings, where the Bi-LSTM model closely mirrors actual stock prices, beginning and ending within a minimal error range. In contrast, the traditional LSTM model exhibited a larger deviation from actual stock prices, leading to a higher error rate. These enhancements demonstrate how the Bi-LSTM can produce forecasts that are more exact and reliable, which makes it a useful tool for monetary businesses and investors looking to make wise choices in an uncertain environment.

Further exploration into integrating additional features, optimizing model parameters, and employing more advanced DL techniques have potential for refining the predictive models. Furthermore, by expanding feature set, the model can extract attributes that influence stock prices, thereby improving its accuracy and reliability. Moreover, adopting more advanced deep learning techniques could further elevate the model's capabilities. Also, hybrid models combining DL with other techniques for feature extraction, could improve their efficiency in identifying complex patterns. These advanced models could also offer better handling of long-term dependencies in the data, which is a crucial aspect of financial time series analysis. The proposed Bi-LSTM model thus represents a significant step forward in financial time series analysis, providing a robust framework for tackling the inherent complexities of stock market forecasting.

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