LSTM-Based Stock Price Prediction: Comparison between NSE Bank and S&P 500 Index

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Abstract: This paper explores the application of Long Short-Term Memory (LSTM) networks for predicting the closing prices of the NSE Bank Index and the S&P 500 Index. The study was begun by preprocessing historical price data, which involves normalization and sequence creation to prepare it for model training. An LSTM model is then constructed and optimized using Keras Tuner to find the best hyperparameters. The analysis demonstrates that the LSTM model significantly outperforms traditional forecasting methods in terms of prediction accuracy. By evaluating the model's performance through mean squared error and visual comparisons of predicted versus actual prices, that LSTM captures complex patterns in time series data more effectively was founded. This study highlights the LSTM model's superior ability to forecast stock prices, making it a powerful tool for financial predictions. The results suggest that LSTM networks should be increasingly utilized in future market forecasting research to achieve more accurate and reliable predictions, providing valuable insights for investors and market analysts.

1 INTRODUCTION

Predicting stock market prices remains a challenging endeavor due to the complex and dynamic nature of financial markets. The inherent volatility and the multitude of factors influencing stock prices, such as market sentiment, economic indicators, and investor behavior, make accurate forecasting a significant challenge.

Recent advancements in Machine Learning (ML) have provided new tools for addressing this challenge, with Long Short-Term Memory (LSTM) networks emerging as a particularly promising approach. Nelson, Pereira, and De Oliveira (2017) demonstrated the effectiveness of LSTM networks in predicting stock prices by utilizing historical data and technical indicators, achieving an average prediction accuracy of 55.9%. Their study highlighted LSTM's ability to capture temporal dependencies and patterns in financial data, showcasing its potential for enhancing forecasting accuracy. Building on this, Bhandari et al. (2022) focused on the S&P 500 index, comparing single-layer and multilayer LSTM models. Their research found that single-layer LSTM models outperformed multilayer models in terms of prediction accuracy, underscoring the efficiency of LSTM in capturing market volatility. Ghosh et al. (2019) extended LSTM applications to the Indian stock market, demonstrating its ability to surpass traditional forecasting methods and handle complex time series data effectively. Similarly, Liu, Liao, and Ding (2018) applied LSTM to stock transactions, emphasizing its suitability for modeling non-linear and dynamic market behaviors. LSTM was explored for predicting stock returns in the Chinese market, showing significant improvements in prediction accuracy over random methods (Chen et al, 2015). However, there are still some deficiencies in relevant experimental studies.

This body of work collectively supports the effectiveness of LSTM networks in financial forecasting, highlighting their ability to analyze historical price data and technical indicators to provide more accurate predictions. Although LSTM model still has certain limitations in predicting stock price trends, such as prediction delay (Wei, 2019), These studies illustrate the transformative potential of LSTM networks in stock market prediction, offering a robust framework for improving forecasting accuracy amidst the inherent complexities of

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financial markets. Therefore, this study aims to forecast the closing prices of two pivotal financial indices: the NSE Bank Index from the National Stock Exchange of India, representing the Indian banking sector, and the S&P 500 Index, a benchmark reflecting the performance of 500 major U.S. companies. Analyzing these indices offers insights into the banking sector's trends within India and broader market dynamics in the United States. The proposed approach not only aims to improve the precision of stock price predictions but also contributes to the broader understanding of advanced forecasting techniques in financial markets.

2 DATA

The data used in this study came from Yahoo Finance(https://finance.yahoo.com/?guccounter=1), a widely used website for financial data. Yahoo Finance provides historical data on multiple stock markets around the world, including important metrics such as daily closing price, opening price, high price, low price, and trading volume. The data was selected covering the period from August 29, 2023, to August 29, 2024. The data in this time range can effectively reflect the long-term trend and volatility of the market, which is helpful for the training and prediction of the model. Among the many available data, the study focuses on “Closing Price” as the main indicator of analysis. Closing price refers to the transaction price of the last transaction of the securities in the trading day, which is the final reflection of the market's trading activities in the day, so it is a common indicator for trend analysis and prediction. Before model training on the data, descriptive statistical analysis was performed on the selected data. Below are the basic statistical characteristics of selected NSEBANK and S&P 500 index data, including mean, standard deviation, minimum, maximum, and quartile ranges. Table 1 shows that the average value of NSEBANK Index is significantly higher than that of S&P 500 index. The average value of the former is 47,365.64, while the average value of the latter is 4959.79. This difference indicates that the overall level of the NSEBANK index was much higher than the S&P 500 index during the study period. In addition, the comparison of the maximum values reflects a similar trend: the maximum value of the NSEBANK index is 53,103.70, which is significantly higher than the maximum value of the S&P 500 index of 5667.20. These values reflect differences in size and volatility between the two, which may be related to the market structure, economic conditions and investor behavior to which they belong (Moghar & Hamiche, 2020; Yadav, Jha & Sharan, 2020).

3 METHODOLOGIES

This paper primarily employs LSTM to forecast the closing price of the NSE Bank and S&P 500 indices. The chapter introduces the LSTM model architecture and the hyperparameter optimization process used to enhance prediction accuracy. Data from the indices is preprocessed and split into training and testing sets. The LSTM model is trained with optimized hyperparameters, and predictions are made for the test period. The performance of the model is evaluated by calculating the Mean Squared Error (MSE) between the predicted and actual values. This article uses this RNN model, the LSTM, with appropriate hyperparameter adjustments to predict future stock trends with high accuracy (Sunny et al, 2020).

Table 1: The basic statistical characteristics of selected data.

INDEX	NSEBANK	S&P 500
Count	365	365
Mean	47365.64	4959.79
Std	2703.57	427.81
Min	42280.15	4117.37
25% quantile	44882.25	4554.89
Median (50%)	47327.85	5035.69
75%quantile	48986.60	5303.27
Max	53103.70	5667.20

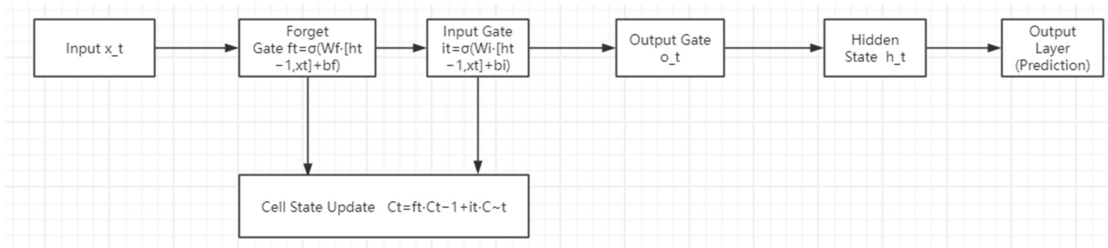

Figure 1: The LSTM model work principle.

Long short-term memory (LSTM) networks are a complex variant of recurrent neural networks designed to deal with sequence prediction problems by learning order dependencies. Their strength lies in their ability to capture both short - and long-term dependencies, which makes them particularly effective in predicting stock prices where past prices have a significant impact on future forecasts (Bhandari et al.,2022). The process follows a structured workflow.

Forget Gate: This Decides how much of your previous memory to forget.

Input Gate: This Decides how much new memory to add to the cell state.

Cell State Update: This Combines the oblivion gate and the input gate to update the cell status.

Output Gate: This Determines how much information is output from the current cell state.

Detailed process can ben seen in Figure 1.

LSTM processes and remembers long-term dependencies in time series data through a series of carefully designed gating mechanisms (Moghar & Hamiche, 2020). At each time step, the LSTM decides what previous information to keep in the cell state through a "forget gate," allowing the model to discard information that is no longer important (Staudemeyer et al., 2019).The input gate determines what new information is important from the current input and combines it with the existing cell state, updating the cell state to incorporate the new important information (Rahman et al., 2016). This updating process involves discarding some old memories and adding new memories provided by the current time step, where the degree of discarding of old memories is controlled by the forgetting gate, and the addition of new memories is determined by the input gate and a candidate memory value. Finally, the "output gate" determines part of the output based on the updated cell state and the current input. Together, these gating mechanisms enable LSTM to effectively retain long-term information while processing sequence data, while forgetting information that is no longer important or relevant to the prediction task, greatly improving its ability to model time series data, especially in scenarios where long-term dependencies need to be understood. This structure enables LSTM to effectively capture long-term dependencies in time series, solving the problem of gradient disappearance or gradient explosion encountered by standard RNNS during training.

4 RESULTS

4.1 Data Processing

The study used closing price data from August 23, 2023, to August 23, 2024. The data was divided into a training set and a test set, where the training set had a time range from August 23, 2023, to June 30, 2024, and the test set had a time range from July 1, 2024, to August 23, 2024.

4.2 Model Training

In order to optimize the performance of the model, hyperparameter adjustment technique is used in this study. A bidirectional LSTM model was used for training and select the optimal hyperparameters through Random Search in the following range (See Table 2).

Table 2: Range of the optimal hyperparameters.

parameter name	range
LSTM units	50-100
Dropout rate	0.3-0.5

Finally, the optimal parameter combination selected by the model is shown in Table 3.

Table 3: The value of the optimal hyperparameters.

parameter name	range
LSTM units	60
Dropout rate	0.4

4.3 NSE Bank

Figure 2 shows the change of mean square error (MSE) of the NSEBANK index during training. During the training, the mean square error (MSE) decreases continuously, indicating that the performance of the model is gradually optimized on the training set. However, fluctuations in validation errors imply the effect of market volatility on model performance. Such volatility may stem from short-term market instability or the risk of overfitting. Overfitting results in a model that performs well on the training set but underperforms when faced with actual test data.

Figure 3 shows the actual price of the NSEBANK index compared to the forecast price. The model can grasp the general trend well, but the prediction error is larger in the high fluctuation region. This error indicates insufficient sensitivity of the model to extreme market volatility, possibly due to the limited capacity of the LSTM model to handle large price changes, or due to the scarcity of such volatility data in the training data. At the same time, although the model performs well against general market trends, its performance is still limited by market fluctuations, especially when prices change sharply.

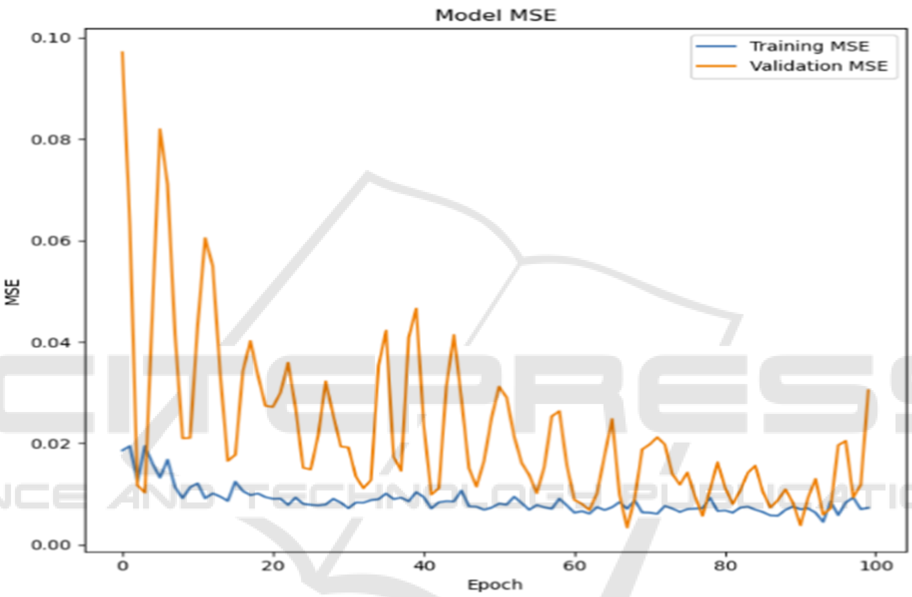

Figure 2: Model MSE(NSEBANK).

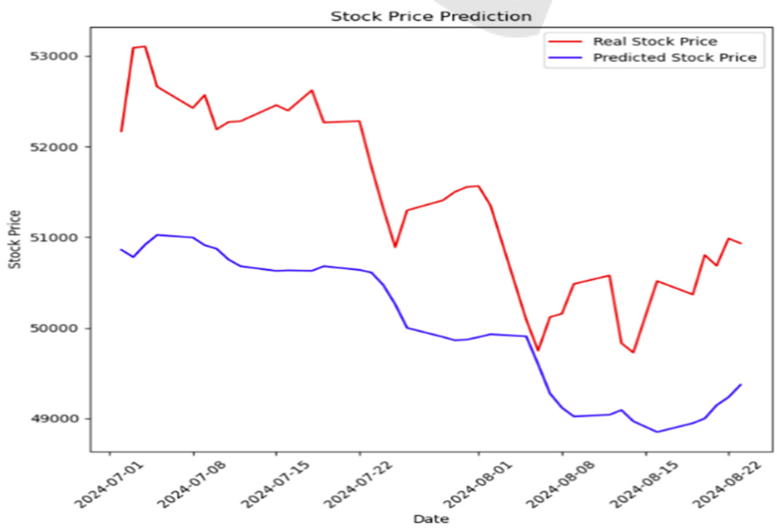

Figure 3: Prediction of NSEBANK.

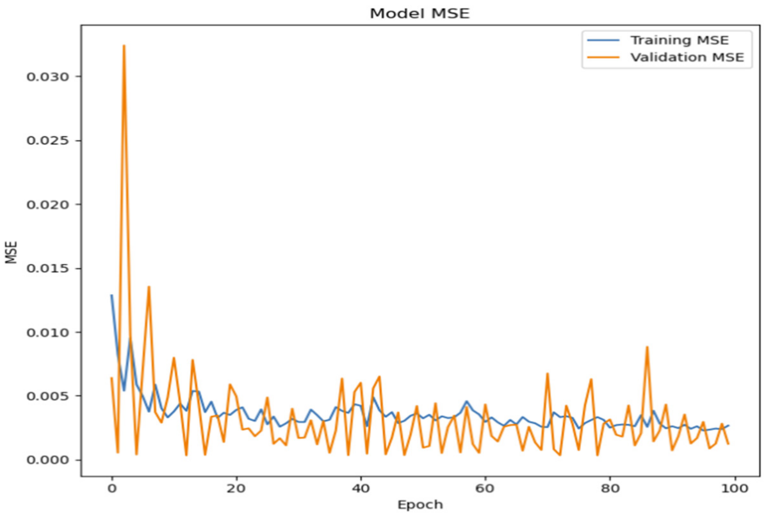

Figure 4: Model MSE (S&P 500).

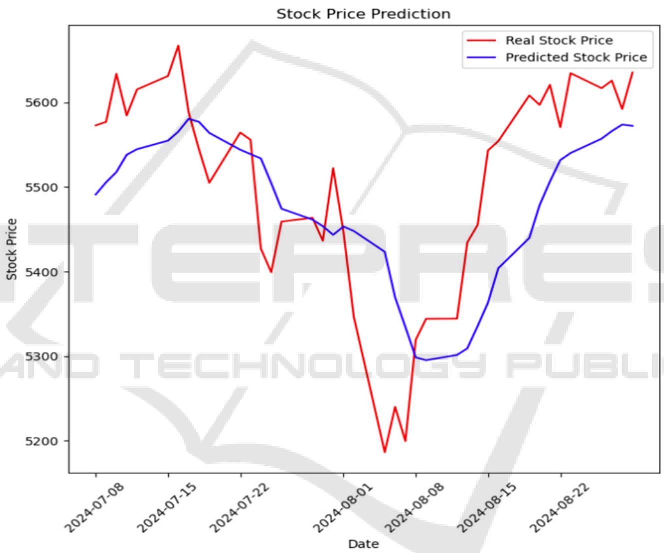

Figure 5: Prediction of SP500.

Table 4 shows the mean square error (MSE) of the NSEBANK index on the test set. The MSE value reflects the prediction error of the model on the test set, and the lower MSE value indicates that the model has better prediction ability.

Table 4: The value of MSE.

evaluation index	value
MSE	0.0054

4.4 S&P 500

Figure 4 shows the change in mean square error (MSE) of the S&P 500 index during training. Similar to the NSEBANK index, both the training error and validation error of the S&P 500 are gradually declining, indicating that the model is gradually converging, but the fluctuations in validation error also reflect changes in the market.

Figure 5 shows the actual stock price of the S&P 500 index versus the forecast price on the test set. The figure shows that the model predicted price is in line with the overall trend of the actual price, but in some areas of high volatility, the forecast error is obvious. This shows that model has limitations when it comes to dealing with wild market movements, especially when prices rise or fall sharply. Such errors may be due to the LSTM model's insufficient capture of short-term volatility data, or these fluctuations occur less frequently in the training set, resulting in poor performance of the model in such situations. Table 5 shows the mean square error (MSE) of the S&P 500 index on the test set. The smaller MSE value indicates that the prediction error of the model is low, indicating that the model has strong prediction ability.

Table 5: The value of MSE.

evaluation index	value
MSE	0.0048

4.5 NSEBANK vs. S&P 500 Index

While the MSE curves for both have similar swings, the S&P 500 appears to have been more volatile. This likely reflects an essential difference between the two indices: the NSEBANK is more regional and influenced by specific industries, while the S&P 500 is more global and diversified and influenced by more macroeconomic factors.

5 CONCLUSIONS

This study investigates the use of Long Short-Term Memory (LSTM) networks for predicting the closing prices of the NSE Bank Index and the S&P 500 Index. The research involved preprocessing historical price data through normalization and sequence creation to prepare it for model training. An LSTM model was developed and optimized using Keras Tuner to identify the most effective hyperparameters. The findings reveal that the LSTM model significantly outperforms traditional forecasting methods in accuracy. By evaluating the model through mean squared error and visual comparisons of predicted versus actual prices, it was demonstrated that LSTM effectively captures complex patterns in time series data. This highlights the LSTM model's superior forecasting ability, suggesting that it is a valuable tool for financial predictions. The results indicate that LSTM networks hold great potential for enhancing future market forecasting, providing valuable insights for investors and market analysts.

While this study demonstrates the advantages of LSTM models in stock price prediction, several areas warrant further investigation. Future research could explore combining LSTM with other advanced algorithms, such as GRU or Transformer models, to assess their performance under varying market conditions. Expanding the scope to include additional financial indicators or longer time periods could help evaluate the model’s robustness and generalizability. Incorporating additional features, such as market sentiment or macroeconomic variables, might further improve prediction accuracy. Lastly, examining the application of LSTM models in real-time trading strategies could offer insights into their practical utility and effectiveness. These future directions will contribute to a deeper understanding of LSTM applications in financial forecasting and advance the field of financial technology.

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