Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7766434

STOCK MARKET PRICE PREDICTION USING BIDIRECTIONAL LONG SHORT-TERM MEMORY BASED ON SEQUENTIAL MODELING

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ABSTRACT
The stock market offers traders a place to invest and trade in shares since it is a dynamic and volatile marketplace. There are various factors that affect a stock's price. Features that are static and dynamic. For traders, being able to forecast the future value of a specific company's stock can be quite advantageous. An input sequence can be mapped to an output sequence using seq2seq modelling. In this research, we propose a method that uses Bi-Directional LSTM based on sequential Modelling to forecast the future Open, High, Close, Low, Volume (OHCLV) value of a stock.Each OHCLV pricing is a separate sequence, and multitask learning aids in illustrating their connections. It is also suggested to use shared workloads and subtasks in a multitasking system to model prices. Stock prices of APPLE from the Yahoo Finance is used. To evaluate the efficiency of the proposed systems, they are compared against various machine learning algorithms. The proposed Sequential multitasking systems comfortably outperform the existing algorithms
Keywords: Stock market,Stock prediction, LSTM, BiLSTM, Sequential modeling, Multitasking.

I. INTRODUCTION

Since the stock market is a dynamic system that is influenced by many different factors, it is challenging to anticipate its future behavior. However, for investors and traders who want to make wise investment decisions, the capacity to foresee stock prices is essential. For many years, researchers in the domains of finance and computer science have been interested in predicting stock market prices. To increase forecast accuracy, several methods and models have been created. We shall examine many approaches to stock market price prediction, their benefits and drawbacks, and any potential applications in the real world.With the rise of algorithmic trading and the application of artificial intelligence (AI) and machine learning (ML) techniques in finance, the significance of stock market price prediction has risen in recent years. This cutting-edge technology may increase the accuracy of predictions and reveal lucrative trading possibilities. However, they also bring along fresh difficulties like model complexity and overfitting. Therefore, it is crucial to assess these strategies' efficacy in the context of stock market price prediction and contrast them with conventional approaches. The ethical issues surrounding the use of AI and ML in finance as well as their effects on the efficiency and stability of the market will also be covered in this paper.
It [1] proposes a novel approach for stock price prediction called S_I_LSTM, which combines multiple data sources and sentiment analysis using a Long Short-Term Memory (LSTM)

model. The aim is to improve the accuracy of stock price forecasting by incorporating both financial and non-financial information, such as news articles and social media sentiment.While the proposed S_I_LSTM model shows promising results in stock price prediction, there are several limitations to consider. One of the main challenges is the quality and reliability of the non-financial data sources, such as news articles and social media sentiment, which can be biased or contain inaccuracies. Additionally, the model may struggle to capture sudden and unexpected events that can significantly impact the stock market, such as natural disasters or political crises. Finally, the S_I_LSTM model may require substantial computational resources and expertise to implement and maintain, making it less accessible for smaller investors or companies.

As [2] The Indian stock market, represented by the NIFTY50 index, is a vital component of the country's economy and attracts significant attention from investors and analysts. This paper proposes a stock market analysis and prediction approach for the NIFTY50 using a Long Short-Term Memory (LSTM) deep learning model. The model utilizes historical stock prices, trading volume, and technical indicators to forecast future market trends and identify potential investment opportunities. The proposed approach aims to improve prediction accuracy and support informed decision-making for investors and traders.While the LSTM-based approach offers several advantages over traditional stock market prediction methods, there are several limitations to consider. One significant limitation is the requirement for a large amount of historical data to train the model effectively, which can be challenging to obtain, particularly for new companies. Moreover, the model may struggle to capture sudden and unexpected events, such as economic recessions, that can significantly impact the stock market. Additionally, the proposed approach does not consider the influence of external factors, such as political events or natural disasters, which can have a considerable effect on the market. Therefore, the results obtained from this approach should be considered alongside other sources of information and analysis to support informed decision-making.

The [3] While the survey provides valuable insights into the application of machine learning techniques in stock price prediction, there are several limitations to consider. One of the primary limitations is the lack of standardization in the evaluation of prediction models, making it challenging to compare different approaches' performance accurately. Additionally, the survey mainly focuses on technical analysis indicators and financial data sources, neglecting the potential benefits of incorporating non-financial information such as news articles and social media sentiment. Furthermore, the survey does not consider the ethical and regulatory implications of using machine learning techniques in finance, such as algorithmic bias and market manipulation. Finally, the survey may not reflect the latest developments and emerging trends in the field of stock price prediction, given the dynamic and rapidly evolving nature of machine learning research.

SLR [4] Social media platforms have become a rich source of information for investors and traders, providing real-time access to news, opinions, and sentiments related to stock markets. This paper proposes a novel approach for stock price prediction using social media data. The model leverages natural language processing (NLP) and sentiment analysis techniques to extract relevant information from social media posts and incorporate it into a predictive model. The goal is to improve the accuracy of stock price forecasting and support informed decision-making for investors and traders.While the proposed approach shows promise, there are several limitations to consider. Firstly, the quality and reliability of social media data can vary widely, and it can be challenging to distinguish between reliable and unreliable sources. Additionally, social media data is often noisy and subject to bias, which can lead to inaccurate predictions. The model may also struggle to capture sudden and unexpected events, such as natural disasters or political crises, that can significantly impact the stock market. Moreover, the ethical and regulatory implications of using social media data in finance are still being debated, with concerns about privacy, security, and algorithmic bias. Finally, the proposed approach may require significant computational resources and expertise to implement and maintain, making it less accessible for smaller investors or companies.

In [5] The stock market is a complex and dynamic system that is challenging to predict accurately. This paper proposes a novel approach for stock market prediction using Recurrent Neural Networks (RNNs). The model leverages the sequential nature of stock price data and incorporates multiple features, including technical indicators, economic indicators, and sentiment analysis, to forecast future market trends. The proposed approach aims to improve prediction accuracy and support informed decision-making for investors and traders.While the proposed RNN-based approach offers several advantages over traditional methods, there are several limitations to consider. Firstly, the model may require significant computational resources and expertise to implement and maintain, making it less accessible for smaller investors or companies. Additionally, the RNN model may struggle to capture sudden and unexpected events that can significantly impact the stock market, such as natural disasters or political crises. Moreover, the model's accuracy may be limited by the quality and reliability of the data sources used, particularly for non-financial information such as news articles and social media sentiment. Finally, the proposed approach does not consider the influence of external factors, such as political events or regulatory changes, which can have a considerable effect on the market. Therefore, the results obtained from this approach should be considered alongside other sources of information and analysis to support informed decision-making.

In [6] The stock market is influenced by a variety of factors, including economic indicators, news events, and social sentiment. This paper proposes a novel approach for stock market prediction using sentimental analysis and machine learning techniques. The model leverages natural language processing (NLP) to extract relevant information from news articles and social media posts and incorporates it into a predictive model. The goal is to improve the accuracy of stock market forecasting and support informed decision-making for investors and traders.While the proposed approach shows promise, there are several limitations to consider. Firstly, the quality and reliability of data from news articles and social media platforms can vary widely, and it can be challenging to distinguish between reliable and unreliable sources. Additionally, social media data is often noisy and subject to bias, which can lead to inaccurate predictions. Moreover, the model may struggle to capture sudden and unexpected events, such as natural disasters or political crises, that can significantly impact the stock market. Additionally, the ethical and regulatory implications of using sentimental analysis and machine learning techniques in finance are still being debated, with concerns about privacy, security, and algorithmic bias. Finally, the proposed approach may require significant computational resources and expertise to implement and maintain, making it less accessible for smaller investors or companies.

In [7] Stock market crashes can have significant financial and economic consequences, and accurately predicting market trends during these periods is a challenging problem. This paper proposes a robust deep learning model for predicting the trend of stock market prices during market crash periods. The model leverages a combination of convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to capture the complex temporal dependencies in the stock market data. The proposed approach aims to improve prediction accuracy during market crash periods and support informed decision-making for investors and traders.While the proposed deep learning model offers several advantages over traditional methods, there are several limitations to consider. Firstly, the model's performance may be limited by the quality and reliability of the data sources used, particularly during market crash periods when the data can be highly volatile and noisy. Additionally, the model may struggle to capture sudden and unexpected events that can significantly impact the stock market, such as natural disasters or political crises. Moreover, the proposed approach does not consider the influence of external factors, such as political events or regulatory changes, which can have a considerable effect on the market. Furthermore, the model's complexity may require significant computational resources and expertise to implement and maintain, making it less accessible for smaller investors or companies. Finally, the proposed approach may not be applicable to other financial markets, as it may not generalize well to different market conditions or financial instruments.

In [8] The stock market is a complex and dynamic system that is challenging to predict accurately. This paper proposes a stock price prediction model based on Long Short-Term Memory (LSTM) deep learning techniques. The LSTM model is designed to capture the sequential nature of stock price data and incorporate multiple features, including technical indicators, economic indicators, and news events. The goal of the proposed approach is to improve prediction accuracy and support informed decision-making for investors and traders.While the proposed LSTM-based approach offers several advantages over traditional methods, there are several limitations to consider. Firstly, the model's accuracy may be limited by the quality and reliability of the data sources used, particularly for non-financial information such as news articles and social media sentiment. Additionally, the model may struggle to capture sudden and unexpected events that can significantly impact the stock market, such as natural disasters or political crises. Moreover, the proposed approach does not consider the influence of external factors, such as political events or regulatory changes, which can have a considerable effect on the market. Furthermore, the LSTM model may require significant computational resources and expertise to implement and maintain, making it less accessible for smaller investors or companies. Finally, the proposed approach may not generalize well to different market conditions or financial instruments, and the performance of the model may deteriorate over time as market dynamics change.

In [9] Accurately predicting stock prices is a challenging problem that has attracted considerable research attention in recent years. This paper proposes a hybrid approach that combines Long Short-Term Memory (LSTM) deep learning and Autoregressive Integrated Moving Average (ARIMA) time series modeling to predict stock prices. The LSTM model captures the complex temporal dependencies in the data, while the ARIMA model accounts for seasonality and trends. The proposed approach aims to improve prediction accuracy and support informed decision-making for investors and traders.While the proposed LSTM-ARIMA hybrid approach offers several advantages over traditional methods, there are several limitations to consider. Firstly, the model's accuracy may be limited by the quality and reliability of the data sources used, particularly for non-financial information such as news articles and social media sentiment. Additionally, the model may struggle to capture sudden and unexpected events that can significantly impact the stock market, such as natural disasters or political crises. Moreover, the proposed approach does not consider the influence of external factors, such as political events or regulatory changes, which can have a considerable effect on the market. Furthermore, the hybrid model's complexity may require significant computational resources and expertise to implement and maintain, making it less accessible for smaller investors or companies. Finally, the proposed approach may not generalize well to different market conditions or financial instruments, and the performance of the model may deteriorate over time as market dynamics change.

In [10] The stock market is a complex and dynamic system that is challenging to predict accurately. This paper proposes a stacked bidirectional long short-term memory (BLSTM) deep learning model for stock market analysis. The model leverages the power of BLSTM to capture the complex temporal dependencies in the stock market data and improve prediction accuracy. The proposed approach aims to support informed decision-making for investors and traders. While the proposed BLSTM model offers several advantages over traditional methods, there are several limitations to consider. Firstly, the model's accuracy may be limited by the quality and reliability of the data sources used, particularly for non-financial information such as news articles and social media sentiment. Additionally, the model may struggle to capture sudden and unexpected events that can significantly impact the stock market, such as natural disasters or political crises. Moreover, the proposed approach does not consider the influence of external factors, such as political events or regulatory changes, which can have a considerable effect on the market. Furthermore, the BLSTM model may require significant computational resources and expertise to implement and maintain, making it less accessible for smaller investors or companies. Finally, the proposed approach may not generalize well to different market conditions or financial instruments, and the performance of the model may deteriorate over time as market dynamics change.

In [11] Accurately predicting stock trends is a crucial problem that has received considerable attention in recent years. This paper proposes a deep learning approach that combines Long Short-Term Memory (LSTM) neural networks with stock prices and indices to predict stock trends. The LSTM model captures the sequential nature of the stock market data and incorporates multiple features, including technical indicators, economic indicators, and news events. The proposed approach aims to improve prediction accuracy and support informed decision-making for investors and traders.While the proposed LSTM-based approach offers several advantages over traditional methods, there are several limitations to consider. Firstly, the accuracy of the model may be limited by the quality and reliability of the data sources used, particularly for non-financial information such as news articles and social media sentiment. Additionally, the model may struggle to capture sudden and unexpected events that can significantly impact the stock market, such as natural disasters or political crises. Moreover, the proposed approach does not consider the influence of external factors, such as political events or regulatory changes, which can have a considerable effect on the market. Furthermore, the LSTM model may require significant computational resources and expertise to implement and maintain, making it less accessible for smaller investors or companies. Finally, the proposed approach may not generalize well to different market conditions or financial instruments, and the performance of the model may deteriorate over time as market dynamics change.

An input sequence of data can be mapped to an output sequence of data using Sequence to Sequence (Seq2Seq) modelling [14]. An encoder-decoder structure is used by the Seq2Seq models [15]. The decoder creates the corresponding output sequence, and the encoder helps map the structure of the input sequence. Recurrent Neural Networks (RNN) are used by the encoder and decoder to analyze the data's sequence [16]. An RNN type called bidirectional LSTMs (Bi-LSTM) [17] maps the sequences in both forward and backward orientations. This aids the network in managing longer sequences and enduring dependencies.This research suggests a Bi-directional LSTM (Bi-LSTM) model that maps the input sequence of OHLC prices for a specific day. The goal of the suggested Seq2Seq model is to provide an output sequence of OHLC data for the day being investigated. The future price is just as significant in stock price predictions as the previous price.

Bi-LSTMs are used to model both the past and future prices using a window-based approach [18].A machine learning approach called multitask learning [19] performs well when the parameter space contains interconnected parameters.

It is comparable to how people learn new things. People can use gears, clutches, accelerators, etc. when they learn to drive a car, for instance. They can learn to ride a motorbike with the use of this expertise. Through collaborative learning, it is possible to increase performance by learning to solve overlapping subproblems and applying the skills developed while resolving one subproblem to another subproblem.

II. METHODOLOGY

Dataset Description:

Every company registered on a stock market has readily accessible stock pricing. The APPLE of NASDAQ stock values are used in this study. The stock price data was gathered between 2013 and 2018. As shown in Table I, the dataset has four primary features: Open, High, Low, Close, Volume. (OHLCV).

Table1: Described Data Attributes

S.No.	**Feature**	**Description**
1	OpenPrice	Openingpriceofthestockon aparticular day
2	Close Price	Theclosingpriceofthestockattheend ofatradingday
3	HighPrice	Thepeakpriceonaparticularday

4	LowPrice	Thelowestpriceofthestockona particularday
5	Volume	Number of shares traded in a day

Preprocessing the Dataset :

The dataset collected has OHLCV prices samples. The dataset was split into a training and testing set with a ratio of 75:25. The dataset is cleaned to remove any null values. The data is then normalized using the MinMaxScaler of sklearn. This scaling subtracts the minimum value in the dataset from every value in the dataset, and divides every value in the dataset by the maximum value in the dataset. This procedure was repeated across multiple time series, each of which denoted Opening Price, Closing Price, High Price, and Low Price, Volume.

Sequential Modeling and setting up Bi-directional LSTM Encoder – Decoder :

The goal of sequence-to-sequence modelling is to predict the subsequent output of a succession of inputs [22]. Using a predetermined input sequence, Seq2Seq modelling attempts to predict the output sequence [23]. The issue that Sequential mapping solves is the ability to map variable-length sequences to the output sequence. Sequential models are useful for a wide range of activities, especially those that call for the creation of text, sequences, etc. [24].There is a method to solve Sequential predictions called encoder-decoder [25]. A variable-length input sequence is converted by the encoder into a fixed-length vector, which the decoder then decodes. Using the encoded input, the decoder tries to predict the output sequence. Variable length sequences can be mapped using this method.The Sequential model's overall architecture is depicted in Figure 1. Each day's OHLCV stock prices are organized into a sequence. A certain window length of days' worth of OHLCV prices are used as the input sequence. The OHLCV price sequence for the day after the input window is the output sequence. Each Bi-LSTM unit in the encoder maps the Open, Close, High, and Low prices, Volume. The Bi-LSTM units make an effort to simulate the relationship between the past and future sequences. The encoder receives a series of window length units at a specific time. The window length is selected to have the lowest possible output prediction error. The encoder transforms the input sequence into a vector of fixed length. The LSTM units of the decoder decode this vector. A single sequence of OHLCV prices is attempted to be predicted by the decoder.

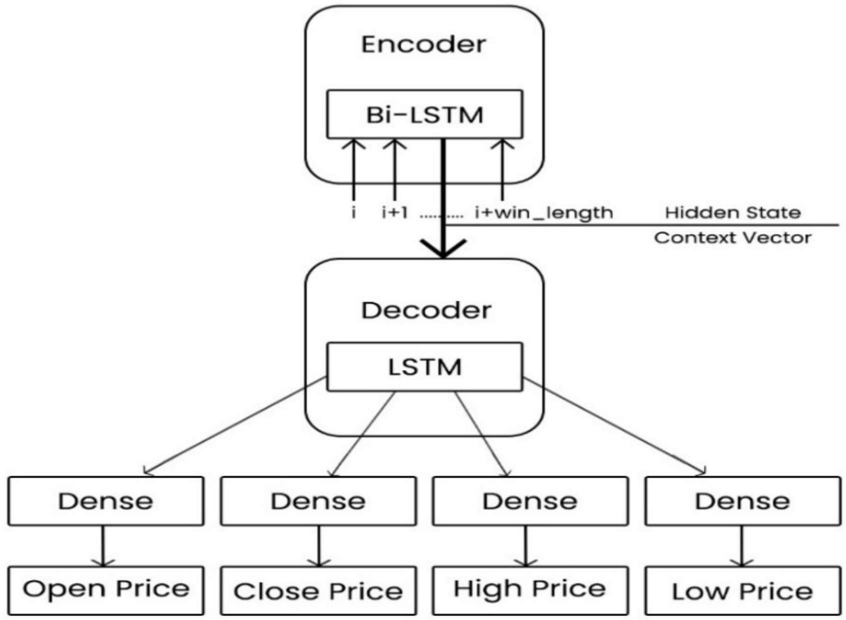


Figure. 1: Implementation of Sequential Model

Algorithm 1:

ALGORITHM FOR SEQUENTIAL MODELING

```
Function seq2seq()
    Data ←MinMaxScalar(data)
    For i in range(windowlength, len(data)) do
        Train_x.append(data[i-window_length:i,:]
        Train_y.append(data[i-1:i,:]
    end
end
```

Determining the Sliding Window:

The use of a sliding window resulted in the creation of an OHLC pricing series. A window size of was chosen as the input for all the values at each time step, and the value after it, $i + 1^{th}$ was chosen as the output.

Bi-LSTM based Multitask Model:

Multitask learning entails learning smaller tasks and then using the knowledge gained to train a larger, shared task [26]. Each of the OHLC prices is taken into account as a subtask in the

implemented system shown in Figure 2. Use of a sliding window with a specific window length is used to prepare the input sequence. The window length is selected to minimise loss. For each price, n-length sequences are trained, and the result is the The n+ 1^{th} price in the list. Using a Bi-LSTM model, each subtask is represented. A common Bi-LSTM model receives the outputs from all of the various subtasks and concatenates them to forecast the output sequence for each of the OHLC prices.
Each subtask in the multitask model uses a Bi-LSTM model to try to learn each of the OHLC prices. There are two Bi-LSTM layers for each subtask, each with 128 and 64 nodes. Figure 8 demonstrates that 2 hidden layers have the lowest RMSE. A dropout of 0.2 follows each Bi-LSTM layer.
A 4 * 1 dimensional vector that forecasts open, close, high, and low prices is the result of the four subtasks. A shared task that attempts to further reduce the loss of predictions receives this output vector as input. Two dense layers, each with 100 and 50 nodes, make up this shared work. Figure 9 demonstrates that the shared job with two hidden layers has the lowest RMSE.As shown in Figure 7, the shared job is mapped to the OHLC pricing using four output Dense layers.Five epochs are used to train the multitask model.

Algorithm 2 shows how the dataset is created for the Multitask model. The training set is taken as a sequence of determined window size. The training outputs are segregated separately for OHLC prices. This is because prediction of each price forms a sub task in the multitask model.

Algorithm 2:

ALGORITHM FOR MULTITASKING MODEL

```
Function Multitask()
Data ←MinMaxScalar(data)
For i in range(window_length, len(data)) do
    train_x.append(data[i-window_length:i,:]
    train_y_open.append(data[i,0])
    train_y_close.append(data[i,0])
    train_y_high.append(data[i,0])
    train_y_low.append(data[i,0])
end
end
```

Bi-LSTM based Multitask Model:
The parameters used to train the models are displayed in Table II. RMSProp is the optimizer in use [27]. The gradient is divided by the moving average's root using RMSProp, which keeps a moving average of the gradient values' square values. When training the model over the generated data, a learning rate of 0.001 was employed. The mean squared error loss function

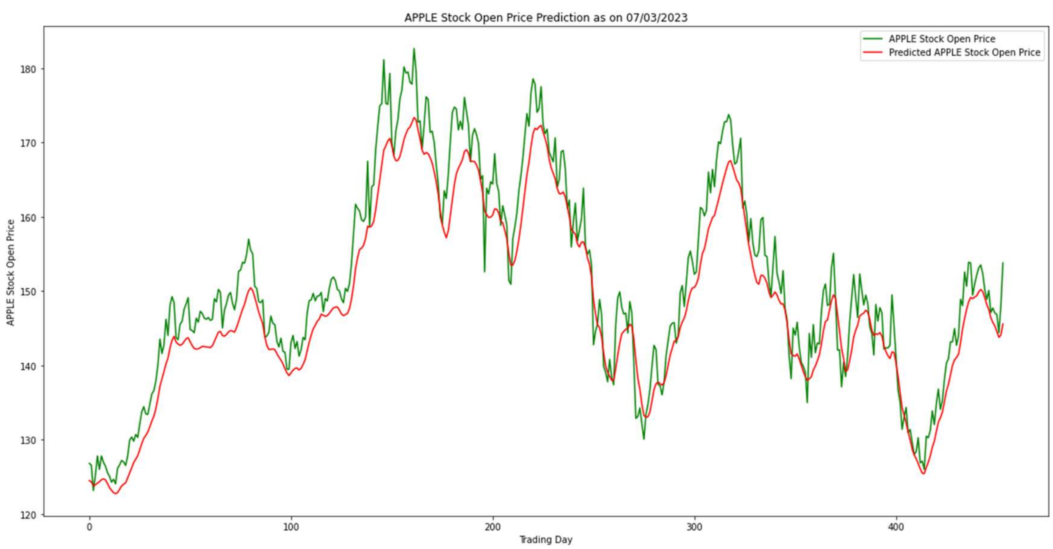
[28], which calculates the mean of the squared difference between the label and predictions, was the loss function that was employed. To prevent both positive and negative loss differences throughout the dataset from being neutralized, the squared difference is calculated.

Parameters:

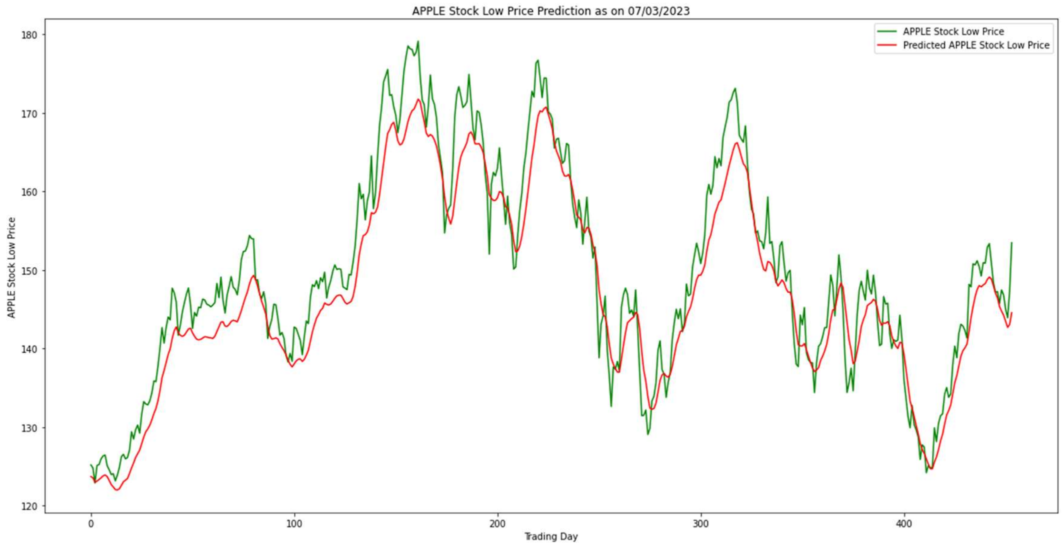
Table 2: Described Parameters

S.No.	Parameter	Value
1	Optimizer	RMSProp
2	Loss Function	MeanSquaredError
3	LearningRate	0.001
4	BatchSize	32

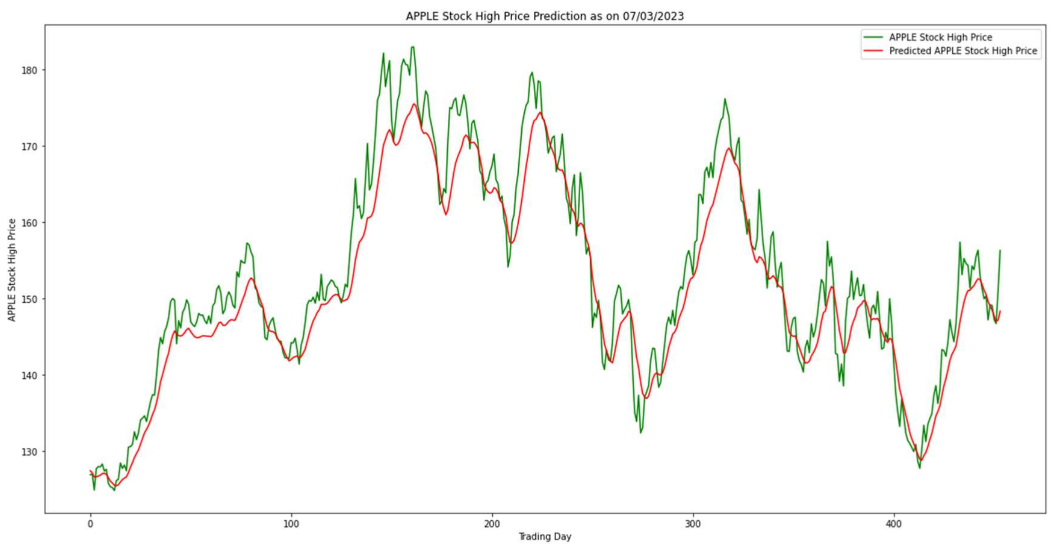
III. Results And Analysis



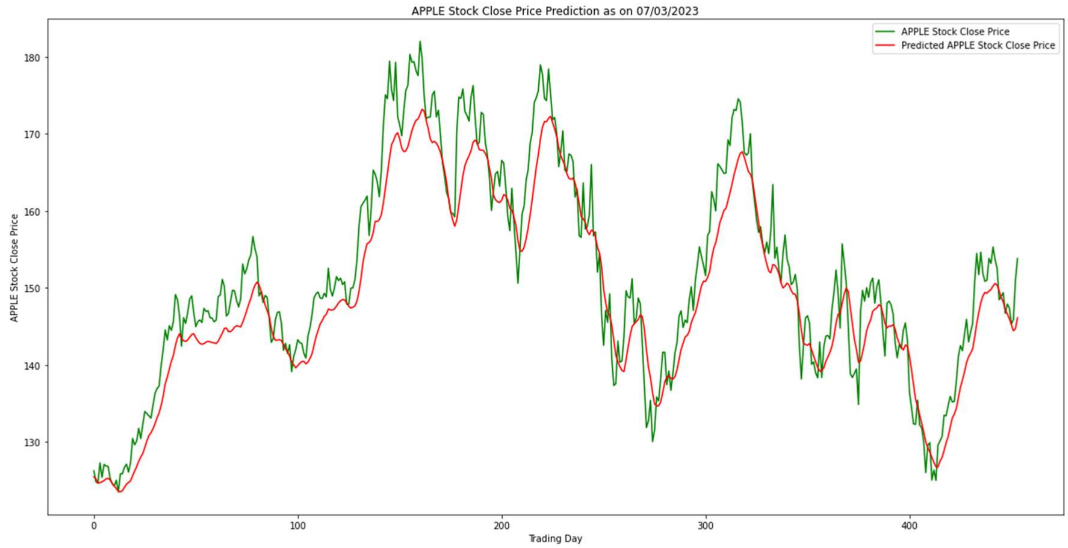
(a)


APPLE Stock Low Price Prediction as on 07/03/2023
APPLE Stock Low Price
Predicted APPLE Stock Low Price
APPLE Stock Low Price
Trading Day

(b)


APPLE Stock High Price Prediction as on 07/03/2023
APPLE Stock High Price
Predicted APPLE Stock High Price
APPLE Stock High Price
Trading Day

(c)



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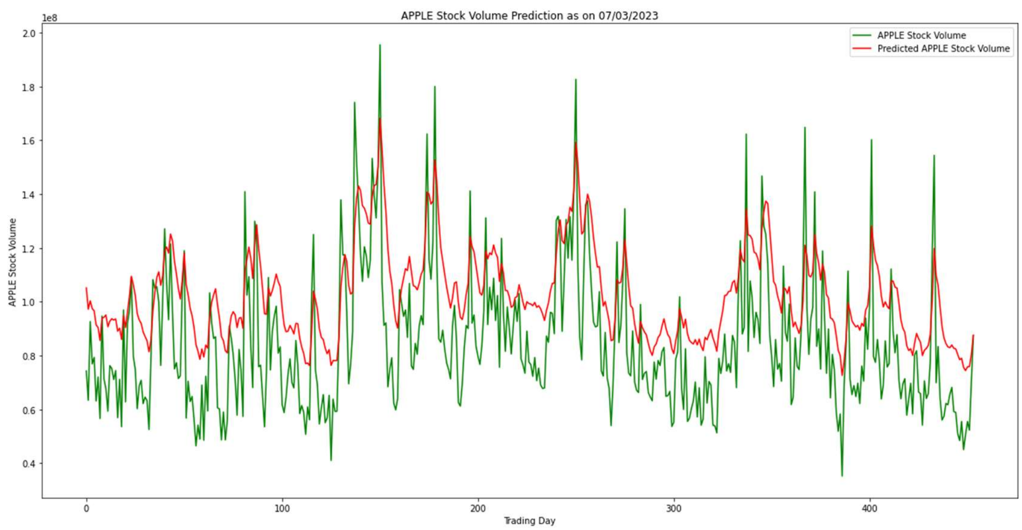


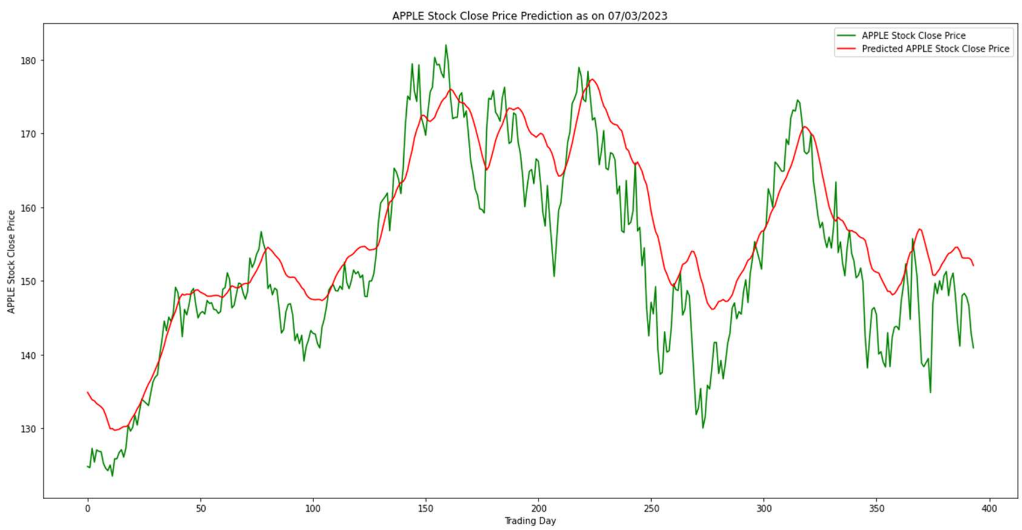
(e)

FIGURE. 2: PREDICTION GRAPHS FOR A) OPEN B) CLOSE C) HIGH AND D) LOW E) VOLUME BY BI-LSTM BASED SEQ2SEQ MODEL

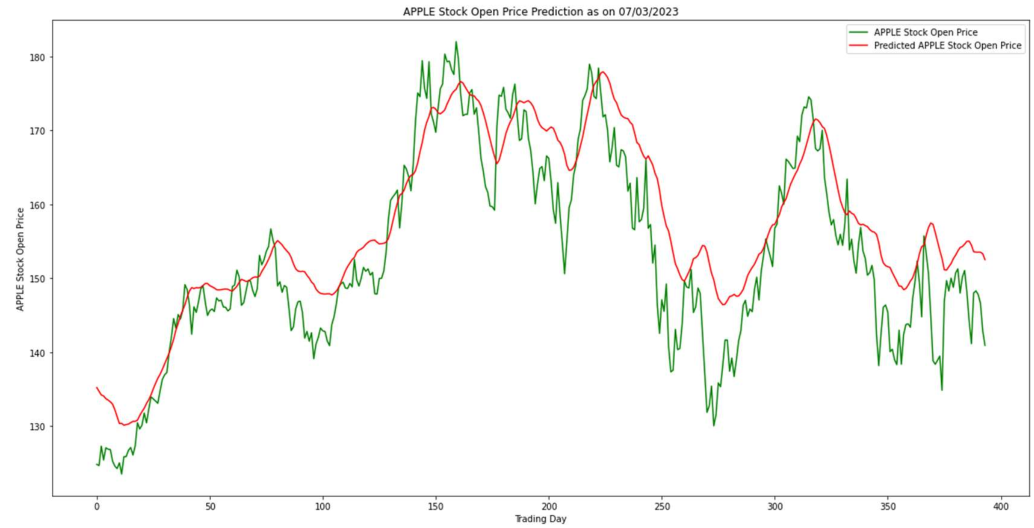
The prediction graphs for OHLCV data and OHLC for both models are shown in Figures 2,The orange line displays the projected data, and the green line displays the actual data. The accuracy of the models' output predictions depends on how closely the two lines are spaced. Evaluating the performance of the suggested model is fundamental and crucial for any machine learning challenge. The suggested system is assessed using the metrics listed below, where "n" denotes the quantity of observations and "yi" denotes theexpected price of the stock, while xi stands for the stock's actual value.


APPLE Stock High Price Prediction as on 07/03/2023
APPLE Stock High Price
Predicted APPLE Stock High Price
APPLE Stock High Price
Trading Day

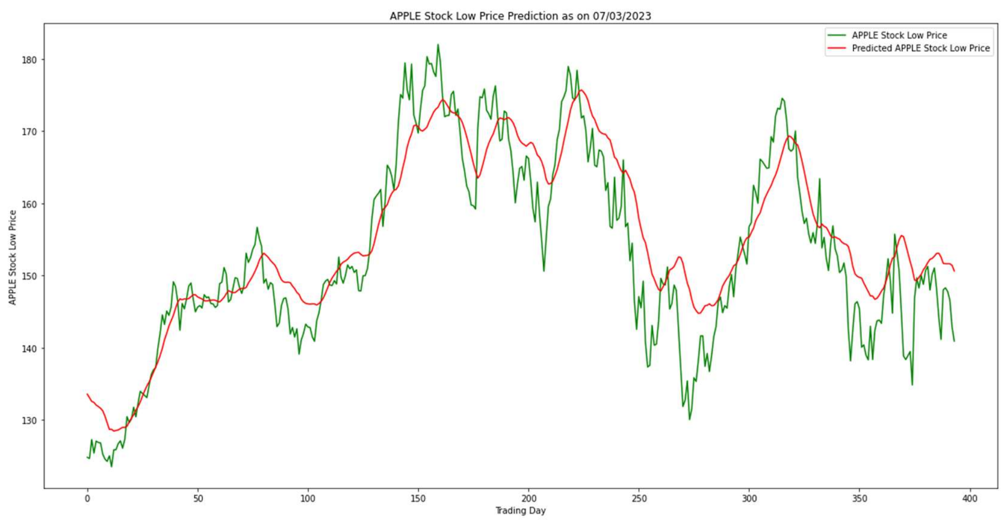
(A)


APPLE Stock Close Price Prediction as on 07/03/2023
APPLE Stock Close Price
Predicted APPLE Stock Close Price
APPLE Stock Close Price
Trading Day

(B)



(C)



(D)

IV. MODEL EVALUATION METRICS

Numerous indicators are available to assess machine learning models in diverse applications. Let's examine the evaluation metrics to evaluate a machine learning model's performance. This is essential in any data science project because it seeks to estimate a model's generalization accuracy on future data.

A. Mean Absolute Error

Mean absolute error gives the mean of absolute difference between model prediction and target value.

$$Mean\ Absolute\ error = \frac{1}{n}\sum_{i=1}^{n}|x_i - x|$$

B. Mean Squared Error

The Mean Squared Error measures how close a regression line is to a set of data points. It is a risk function corresponding to the expected value of the squared error loss. Mean square error is calculated by taking the average, specifically the mean, of errors squared from data as it relates to a function.

$$\textit{Mean Squared error} = \frac{\sum(y_i - \hat{y}_i)^2}{n}$$

C. Root Mean Squared Error

Root Mean Squared Error (RMSE)and Mean Absolute Error (MAE) are metrics used to evaluate a Regression Model. These metrics tell us how accurate our predictions are and, what is the amount of deviation from the actual values.

$$\textit{Root Mean Squared error} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

Table3: Comparison of Proposed Models Against Various Models

Model	MAE	MSE	RMSE
Support VectorMachine	11.5572	223.218	15.103
LassoRegression	11.1023	213.812	14.5814
RandomSampleConsensus	9.4037	188.366	13.6552
TheilSenRegressor	10.1128	185.304	13.5530
HuberRegressor	9.5409	180.94	13.3908
LinearRegression	9.8032	175.807	13.1914
RidgeRegression	9.7545	174.625	13.1467
k-NeighboursRegressor	9.2576	149.553	12.1733
BayesianRidge	9.7404	174.392	13.1391
Bi-LSTMSequentialModel	2.6845	17.760	4.1947
Bi-LSTM Multitasking Model	5.4586	44.1827	6.6303

As can be seem from Table 3, the proposed Seq2Seq model and Bi-LSTM Multitask model comfortably outperform the existing regression models. A low RMSE indicates that the model is predicting the future value with accuracy. As can be seen from Table III, the two proposed models have a significantly low RMSE value in comparison to existing regression algorithms. This demonstrates that the proposed models are able to predict the upward and downward trend of the price of a stock.

V. CONCLUSION

Using a Bi-Directional LSTM based Sequence to Sequence Modeling, a method to forecast the future Open, High, Close, Low (OHCL) price of a stock has been proposed in this research. The APPLE stock price from the NASDAQ is used to test the system. The RMSE values for the Sequential and Multitasking models were 4.19 and 6.63, respectively. The proposed models outperformed a number of other regression models that were already in use. Future testing of the system could include both static and dynamic features. Additionally, sentiment analysis can be used to assess a stock's upward or negative trend by looking at news stories, blogs, social media posts, etc.

REFERENCES

1. Wu, S., Liu, Y., Zou, Z., & Weng, T. H. (2022). S_I_LSTM: stock price prediction based on multiple data sources and sentiment analysis. Connection Science, 34(1), 44-62.

2. Sisodia, P. S., Gupta, A., Kumar, Y., & Ameta, G. K. (2022, February). Stock market analysis and prediction for NIFTY50 using LSTM Deep Learning Approach. In 2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM) (Vol. 2, pp. 156-161).

3. Kumari, J., Sharma, V., & Chauhan, S. (2021, December). Prediction of Stock Price using Machine Learning Techniques: A Survey. In 2021 3rd International Conference on Advances in Computing, Communication Control and Networking (ICAC3N) (pp. 281-284). IEEE.

4. Rajeswar, K. S., Ramalingam, P., & SudalaiMuthu, T. (2021, October). Stock Price Prediction Using social media. In 2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA) (pp. 1-4). IEEE

5. Islam, S. B., Hasan, M. M., & Khan, M. M. (2021, October). Prediction of Stock Market Using Recurrent Neural Network. In 2021 IEEE 12th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON) (pp. 0479-0483). IEEE.

6. Shah, U., Karani, B., Shah, J., & Dhande, M. (2021, October). Stock Market Prediction Using Sentimental Analysis and Machine Learning. In 2021 2nd Global Conference for Advancement in Technology (GCAT) (pp. 1-4). IEEE.

7. Ghasemieh, A., & Kashef, R. (2022, April). A Robust Deep Learning Model for Predicting the Trend of Stock Market Prices During Market Crash Periods. In 2022 IEEE International Systems Conference (SysCon) (pp. 1-8). IEEE.

8. Kavinnilaa, J., Hemalatha, E., Jacob, M. S., & Dhanalakshmi, R. (2021, July). Stock price prediction based on LSTM deep learning model. In 2021 International Conference on System, Computation, Automation and Networking (ICSCAN) (pp. 1-4). IEEE.

9. Mahadik, A., Vaghela, D., & Mhaisgawali, A. (2021, August). Stock Price Prediction using LSTM and ARIMA. In 2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC) (pp. 1594-1601). IEEE.

10. Lim, J. Y., Lim, K. M., & Lee, C. P. (2021, September). Stacked bidirectional long short-term memory for stock market analysis. In 2021 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET) (pp. 1-5). IEEE.

11. Karlis, V., Lepenioti, K., Bousdekis, A., & Mentzas, G. (2021, July). Stock Trend Prediction by Fusing Prices and Indices with LSTM Neural Networks. In 2021 12th International Conference on Information, Intelligence, Systems & Applications (IISA) (pp. 1-7). IEEE.

12. Mathanprasad, L., & Gunasekaran, M. (2022, January). Analysing the Trend of Stock Marketand Evaluate the performance of Market Prediction using Machine Learning Approach. In *2022 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)* (pp. 1-9). IEEE.

13. Vui, C. S., Soon, G. K., On, C. K., Alfred, R., & Anthony, P. (2013, November). A review of stock market prediction with Artificial neural network (ANN). In *2013 IEEE international conference on control system, computing and engineering* (pp. 477-482). IEEE.

14. Patel, R., Choudhary, V., Saxena, D., & Singh, A. K. (2021, June). Review of stock prediction using machine learning techniques. In *2021 5th International Conference on Trends in Electronics and Informatics (ICOEI)* (pp. 840-846). IEEE.

15. Y. Keneshloo, T. Shi, N. Ramakrishnan, and C. K. Reddy, “Deep Reinforcement Learning for Sequence-to-Sequence Models,” IEEE Transactions on Neural Networks and Learning Systems, vol. 31, no. 7,pp. 2469–2489, 2019.

16. K. Palasundram, N. MohdSharef, N. A. Nasharuddin, K. A. Kasmiran,and A. Azman, “Sequence to Sequence Model Performance for Education Chatbot,” International Journal of Emerging Technologies in Learning (iJET), vol. 14, no. 24, p. 56, Dec. 2019.D

17. H. Jain and G. Harit, "An Unsupervised Sequence-to-Sequence Autoencoder Based Human Action Scoring Model," 2019 IEEE Global Conference on Signal and Information Processing (GlobalSIP), Ottawa,ON, Canada, pp. 1-5, 2019.

18. K. A. Althelaya, E.-S. M. El-Alfy, and S. Mohammed, “Evaluation of bidirectional LSTM for short-and long-term stock market prediction,” in 2018 9th International Conference on Information and Communication Systems (ICICS), pp. 151-156, 2018

19. J. Chou and T. Nguyen, "Forward Forecast of Stock Price Using Sliding- Window Metaheuristic-Optimized Machine-Learning Regression," in IEEE Transactions on Industrial Informatics, vol. 14, no. 7, pp. 3132-3142, July 2018.

20. J. Chou and T. Nguyen, "Forward Forecast of Stock Price Using Sliding-Window Metaheuristic-Optimized Machine-Learning Regression," in IEEE Transactions on Industrial Informatics, vol. 14, no. 7, pp. 3132-3142, July 2018.

21. B. Ko and H. Choi, "Paraphrase Bidirectional Transformer with Multitask Learning," 2020 IEEE International Conference on Big Data and Smart Computing (BigComp), Busan, Korea (South), pp. 217-220, 2020.

22. S. Hwang, G. Jeon, J. Jeong, and J. Lee, “A Novel Time Series based Seq2Seq Model for Temperature Prediction in Firing Furnace Process,” Procedia Computer Science, vol. 155, pp. 19–26, 2019.

23. A. Joshi, K. Mehta, N. Gupta and V. K. Valloli, "Data Generation Using Sequence-to-Sequence," 2018 IEEE Recent Advances in Intelligent Computational Systems (RAICS), Thiruvananthapuram, India, pp. 108-112, 2018.

24. G. Aalipour, P. Kumar, S. Aditham, T. Nguyen and A. Sood, "Applications of Sequence to Sequence Models for Technical Support Automation," 2018 IEEE International Conference on Big Data (Big Data), Seattle, WA, USA, pp. 4861-4869, 2018.

25. Y. Chen, W. Lin and J. Z. Wang, "A Dual-Attention-Based Stock Price Trend Prediction Model With Dual Features," in IEEE Access, vol. 7, pp.148047-148058, 2019.

26. G. Balikas, S. Moura, and M.-R. Amini, "Multitask Learning for Fine- Grained Twitter Sentiment Analysis," in Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 1005–1008, 2017.
27. S. V. G. Reddy, K. T. Reddy, and V. ValliKumari, "Optimization of Deep Learning using various Optimizers, Loss functions and Dropout," International Journal of Recent Technology and Engineering (IJRTE), vol. 7, no. 4S2, pp. 448–455, 2018.
28. A. Botchkarev, "A New Typology Design of Performance Metrics to Measure Errors in Machine Learning Regression Algorithms," Interdisciplinary Journal of Information, Knowledge, and Management, vol. 14, pp. 045–076, 2019.