

# An Optimized Deep Learning Model for Stock Price Prediction Using Bi-Directional LSTM with Multi-Inputs and Multi-Steps

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**Abstract.** Predicting stock prices accurately is an inherently challenging task due to the dynamic and fluctuating nature of various influencing factors. However, with the advent and implementation of deep learning, achieving precise stock predictions has become feasible. This study employs Bi-Directional Long Short-Term Memory (LSTM) models to forecast the closing stock price of Tesla for the following day. Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are selected as indicators to show methods' performance. A new variable has been created through open and close stock price. The original method uses close stock prices as the only input for prediction. In contrast, the modified method uses both the open stock price and the created new variable for calculating close stock price. Both methods' parameters are firstly trained and adjusted on training and validation dataset for their best performance. Finally, both methods are applied to test dataset and the value of both indicators depict their prediction performance.

**Keywords:** Deep Learning, BI-LSTM, Stock Prediction.

## 1. Introduction

The stock market stands out as one of the most popular and highly concentrated domains across various social fields. Since there could be huge benefits from accurate prediction on stock price fluctuation, a great number of researchers and specialists devote a lot of time and effort to stock market research [1]. The prediction on stock market, however, is quite challenged [2]. Firstly, stock price can be influenced by multiple factors from both inside and outside stock market fields such as political events, science and technology breakthroughs, relevant companies' events and the national economic circumstances [3]. Moreover, resulting from stock price uncertainty and dynamic characters, the stock price might appear large fluctuations within a period of time which increase the difficulty on precise stock prediction.

Machine learning can be classified as a field of techniques or a practical method which is dedicated to exerting the power of computers on computing for different purposes. As the invention and development of machine learning, it seems that accurate stock price prediction is much more achievable than before. In the past decades, numerous machine learning models and algorithms have been improved and conducted for predicting the stock price such as Random Forest Support Vector Machine, Linear Regression etc. Subsequently, for improving stock prediction accuracy as well as dealing with the increase of parameters' number and ranges, deep learning method could handle multiple various parameters and try different parameters' values combinations [4, 5]. Indeed, deep learning is the most welcome and reliable stock price prediction method today [6]. Recurrent Neural Networks (RNN) is a powerful and prevail deep learning algorithm. RNNs possess the capability of "memory", making them adept at capturing the features of sequential data and making predictions based on the information they have retained. Also, during the process of remembering the feature of consecutive data, a general RNN method tends to give larger weights to nearest data on the sequence input data. Therefore, RNN method is prevailing for predicting stock price [7].

Long Short-Term Memory (LSTM) is a transformed method originating from RNN. Since LSTM introduced three gates (memory gates, forget gates and output gates), it overcomes the RNN problems and has the potential to handle both long and short sequence data [8]. Compared to the machine learning method, LTSM performs much better on predicting the stock price [9, 10]. Bi-Directional

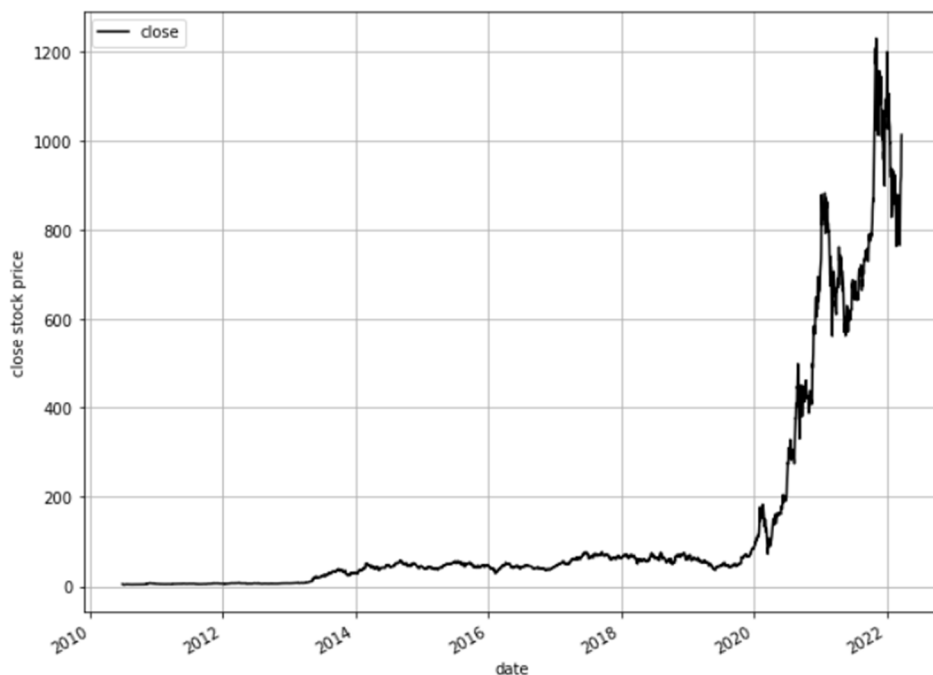
Long Short-Term Memory (BI-LSTM) is a subset transformation of LSTM model which involves two directions' LSTM layer in a neural network. In stock prediction, BI-LSTM also achieved good performance [9, 11].

In this work, the techniques of both LSTM and BI-LSTM have been used to predict the closing stock price of a company. In addition, comparing to using single parameter i.e. close price to predict next single day's close price, a new method by applying open price and a new indicator created by open and close price to predict tested. The effectiveness of models is compared by two performance indicators: Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

## 2. Methodology

### 2.1. Description of Data and Preprocessing

The historical raw data is collected from Kaggle [12]. The dataset includes 12 years data from 6/29/2010 to 3/24/2022 of Tesla. The raw collected data contains information of Tesla which mainly includes Open and Close stock price. Besides, High, Low, Close, adjusted close stock price and daily Volume are also included in the obtained data. Fig.1. shows the close stock price for Tesla from 6/29/2010 to 3/24/2022.



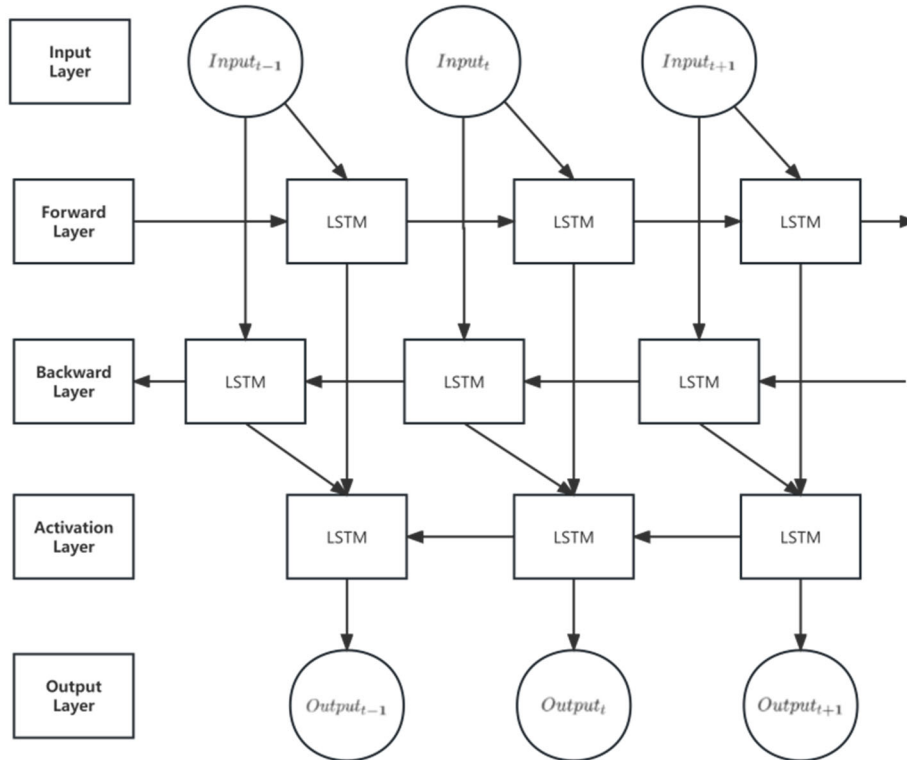
**Figure 1.** Close stock price of Tesla (Photo credit: Original).

For a desired prediction performance and flexible parameter modified strategy, the dataset has been divided into 3 three sections. The early 60% dataset is used for training model and the followed 20% dataset is used for validation as well as choosing the best parameters' combination for methods. The last 20% dataset is used for comparing different methods' prediction performance.

A novel variable has been introduced to predict stock closing prices. This new variable, denoted as "OC" (Open-Close), represents the difference between the stock's closing and opening prices. It is employed as part of the input for the new multiple-input BI-LSTM model.

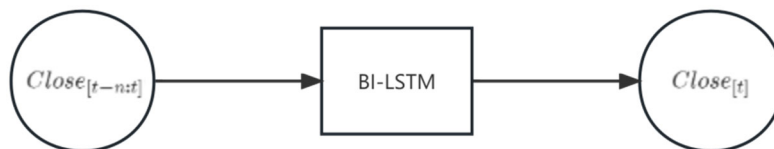
### 2.2. BI\_LSTM Neural Network

In this work, BI-LSTM shown in Fig. 2 is a modified and improved transformation of LSTM which enhances the efficiency on doing time-serial data prediction.

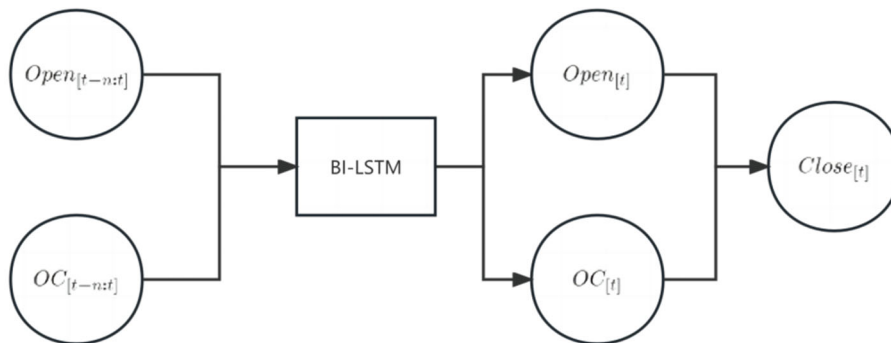


**Figure 2.** Structure of BI-LSTM [9].

In the original method, the input of BI-LSTM method is Tesla’s daily stock price at close and the output of original method is the predicted stock price at close in the next day. In contrast, the multi-input multi-step BI-LSTM method's inputs include Open stock price and OC, the outputs of multi-input multi-step BI-LSTM are the corresponded predicted Open stock price and OC in the next day. The predicted Close stock price of multi-input multi-step BI-LSTM is the sum of predicted Open and OC. The input and output of the original BI-LSTM method and modified method are expressed in Fig. 3 and Fig. 4.

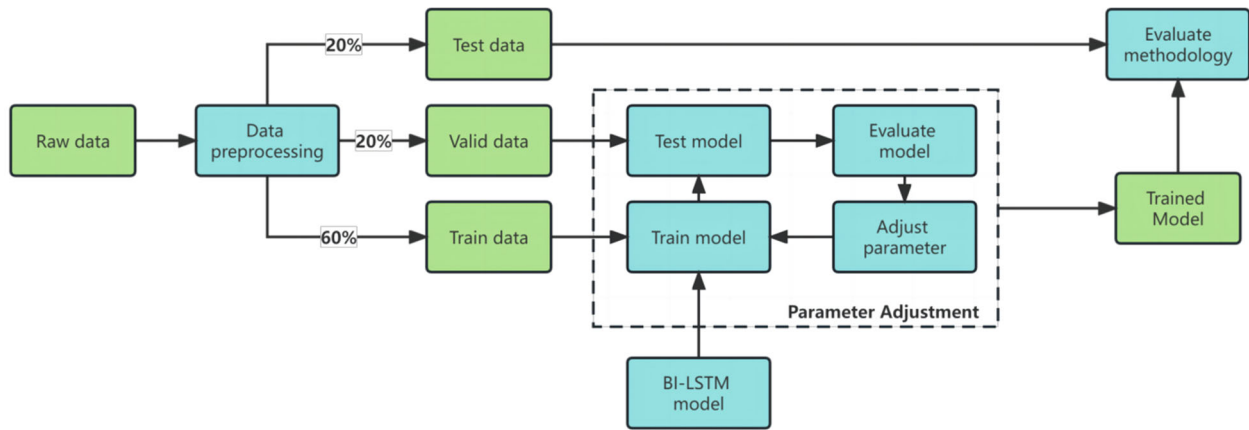


**Figure 3.** Input and output of original BI-LSTM method (Photo credit: Original).



**Figure 4.** Inputs and outputs of multi-input multi-step BI-LSTM method (Photo credit: Original).

The work architecture is depicted in Fig. 5. During the Parameter Adjustment phase, various parameters are experimented with to optimize the performance evaluation for both the original BI-LSTM method and the multi-input multi-step BI-LSTM method. These parameters encompass the number of days for data used in prediction, epochs, batch size, LSTM units for BI-LSTM, dropout probability, and the choice of optimizer.



**Figure 5.** Work architecture of stock close price prediction (Photo credit: Original).

### 2.3. BI\_LSTM Neural Network

There are quite a lot of measures to evaluate the accuracy of a prediction model. In this research, predicted close price is evaluated by RMSE and MAPE. Also, RMSE and MAPE are the indicators for parameter selection in parameter adjustment process. The calculation of RMSE is shown in eq.1.

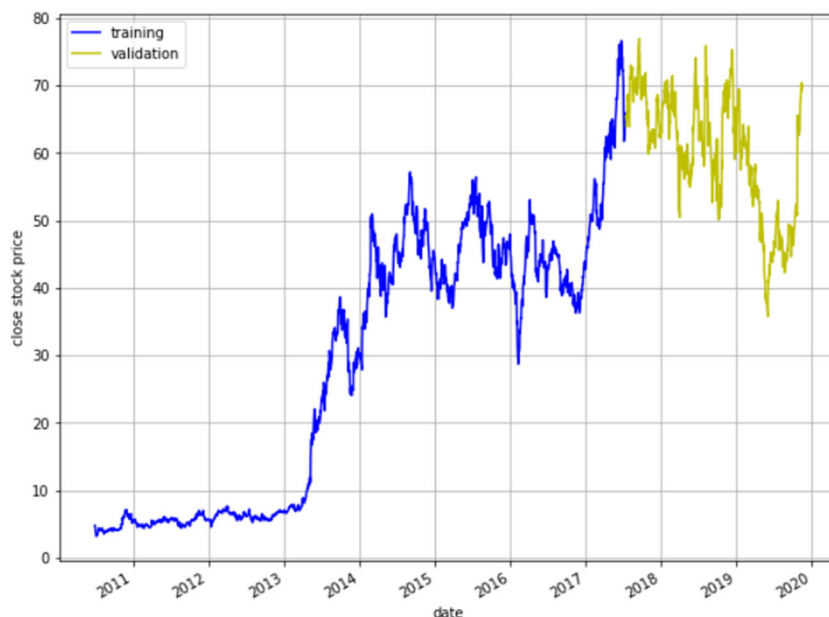
$$RMSE = \sqrt{\frac{\sum_{i=1}^n (A_i - P_i)^2}{n}} \tag{1}$$

Where  $A_i$  refers to the actual close price of predicted day  $i$ ,  $P_i$  refers to the predicted close price of predicted day  $i$  through prediction model. MAPE is another indicator to reflect model's performance. The calculation of MAPE is shown in eq.2.

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{A_i - P_i}{A_i} * 100 \tag{2}$$

Where  $A_i$  refers to the actual close price,  $P_i$  refers to the predicted close price of predicted day  $i$  through prediction model.

### 3. Results and Discussion



**Figure 6.** Actual close stock price of training and validation dataset (Photo credit: Original).

Fig. 6 shows the actual close stock price of the training dataset and validation dataset. After standard scaling, training dataset and observing the data between the actual and predicted data on validation dataset, it can be noticed that the parameters' selection has great impact on models' evaluation measures. Fig. 7 and Fig. 8 illustrate the influence of choosing varying numbers of days as features for both the original BI-LSTM and the multi-input multi-step BI-LSTM methods. In both cases, the original BI-LSTM and the multi-input multi-step BI-LSTM methods exhibit a consistent trend of increased evaluation measures as more days are selected as features. As a result, it is suggested that select 3 days as features.

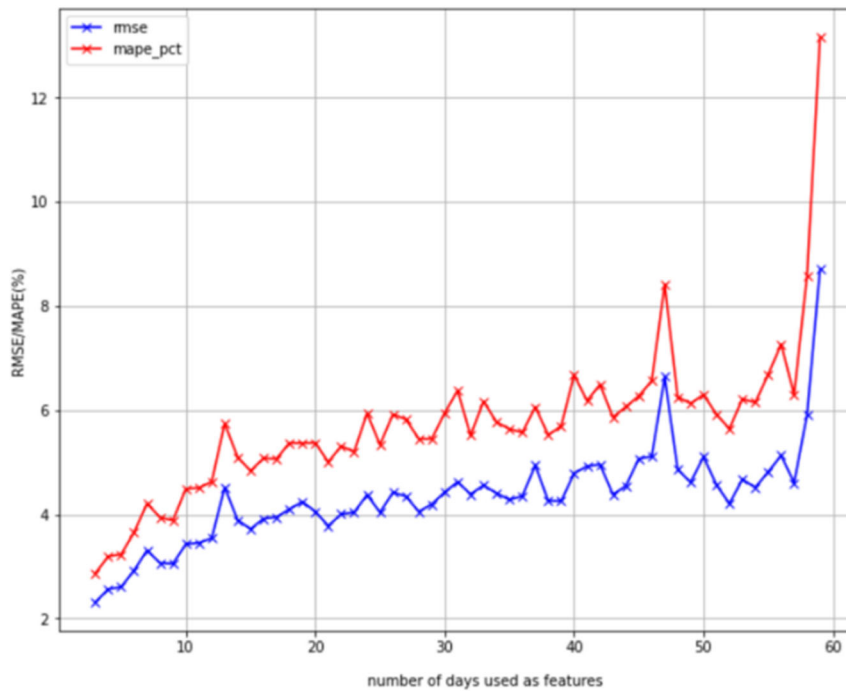


Figure 7. Evaluation measures of original BI-LSTM method with different number of days as features (Photo credit: Original).

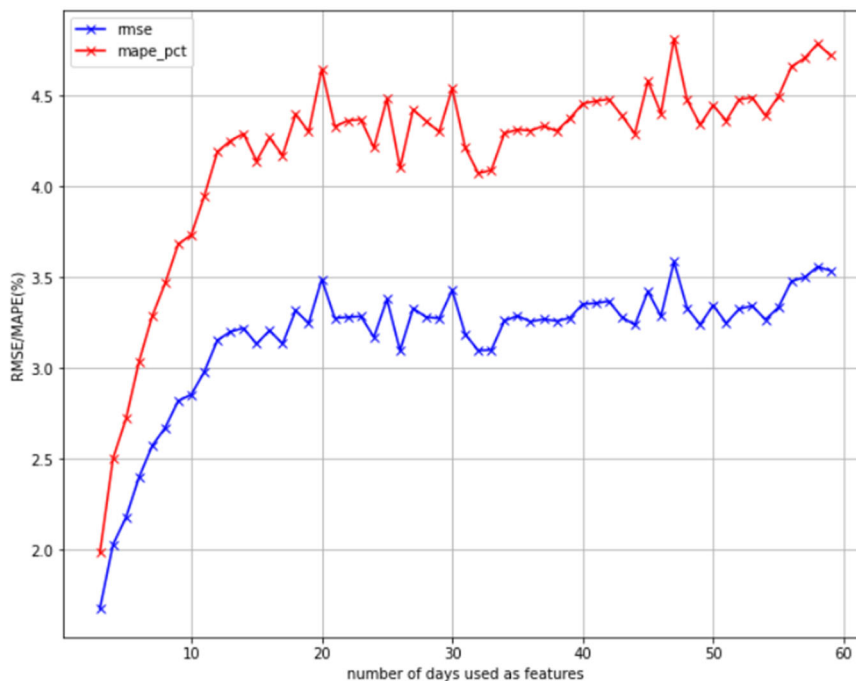


Figure 8. Evaluation measures of multi-input multi-step BI-LSTM method with different number of days as features (Photo credit: Original).

Afterwards, different parameter companions have been tested on original and multiple multi-step BI-LSTM methods. Table 1 shows the different range of parameters tested in the research. Table 2 shows the most appropriate parameters' combination for original and multiple-input multi-step BI-LSTM methods. Table 3. shows original and multiple multi-step BI-LSTM methods' RMSE and MAPE on validation dataset.

**Table 1.** Three Scheme comparing

Parameter	Range
LSTM units	10,50,64,128
Dropout probability	0.5, 0.6,0.7, 0.8, 0.9
Optimizer	adam, sgd, rmsprop, adagrad, adadelata, adamax, nadam
Epochs	1, 10, 20, 30, 40, 50
Batch size	8, 16, 32, 64, 128

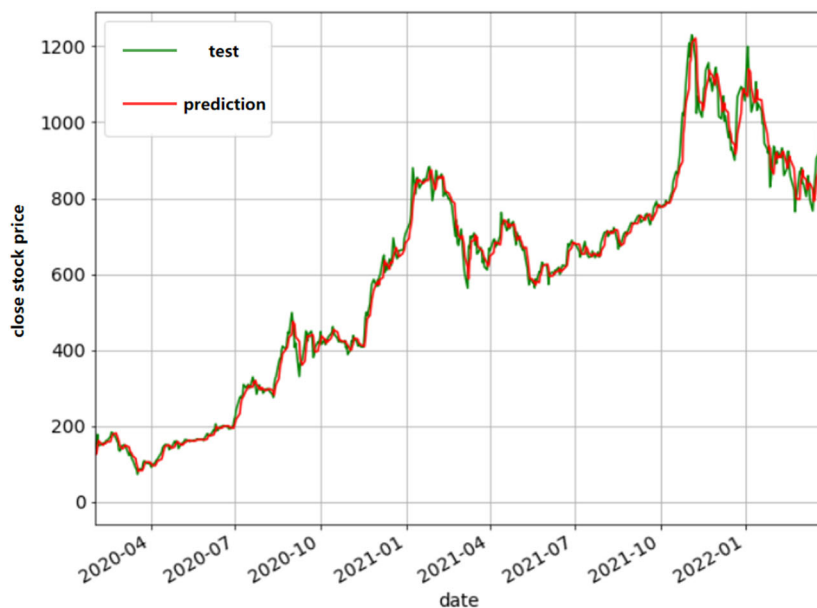
**Table 2.** Parameters' selection for original and multi-input multi-step multi-step BI-LSTM method

Parameter	Original BI-LSTM	multiple-input multi-step BI-LSTM
Number of day as features	3	3
LSTM units	128	10
Dropout probability	0.5	0.8
Optimizer	nadam	adagrad
Epochs	40	1
Batch size	8	64

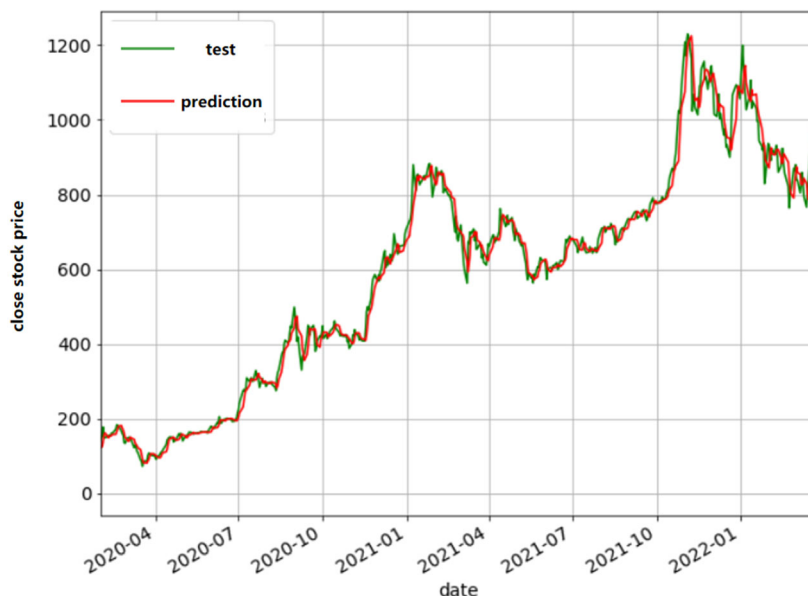
**Table 3.** Original and multi-input multi-step multi-step BI-LSTM methods' RMSE and MAPE on validation dataset

Evaluation measures	Original BI-LSTM	multiple-input multi-step BI-LSTM
RMSE	2.11	1.74
MAPE	2.57%	2.06%

Finally, original and multi-input multi-step BI-LSTM methods have been used to apply on the test data set. Fig. 9 and Fig. 10 show the predicted and actual close stock price on the test dataset.



**Figure 9.** Original BI-LSTM method's close stock price on test dataset (Photo credit: Original).



**Figure 10.** Multi-input multi-step BI-LSTM method's close stock price on test dataset (Photo credit: Original).

**Table 4.** Original and multi-input multi-step BI-LSTM methods' RMSE and MAPE on test dataset

Evaluation measures	Original BI-LSTM	multiple-input multi-step BI-LSTM
RMSE	27.549	23.954
MAPE	3.64%	3.31%

Table 4 shows original and multi-input multi-step BI-LSTM methods' RMSE and MAPE on test dataset. As a result, multi-input multi-step BI-LSTM method has higher accuracy on stock prediction than that of original BI-LSTM which only use historical close price as input.

From Table 3 and Table 4, multi-input multi-step BI-LSTM method provides better prediction on both validation and test dataset. However, the RMSE value of both original and multi-input multi-step BI-LSTM method on test dataset are higher than those of validation dataset. These RMSE differences could be resulted from the differences between training, validation and test dataset. Both training and validation datasets' close stock price fluctuates from roundly 3 to 80. Because the original and multi-input multi-step BI-LSTM methods' model are adjusted and formed according to their performance on training and validation dataset, these models fit the close stock price well. However, the test dataset's close stock price ranges from roundly 65 to 1200 and its degree of rises and drops are quite larger than that of training and validation. Therefore, original and multi-input multi-step BI-LSTM methods show higher RMSE when applying them on test dataset.

#### 4. Conclusion

Deep learning algorithms are very powerful tools when predicting time series value based on the historical records. Predicting stock price is the most rewarded but difficult aspect of applying deep learning algorithms since price value fluctuates all the time. The obtained historical stock price only includes Open, Close, Adjusted close, High, Low stock price and the stock's daily Volume. For increasing prediction accuracy, a new parameter has been introduced into the research. BI-LSTM is the selected deep learning algorithm for stock price prediction. The original method only uses close stock price to predict the future close stock price. In contrast, however, the multi-input multi-step BI-LSTM method uses open price and OC to predict future open and OC value. Following this, the projected closing stock price is determined by combining the predicted open and OC (open-close) prices. To assess the efficacy of the two methods, MAPE and RMSE metrics are employed. The multi-input multi-step BI-LSTM method demonstrates superior predictive performance, yielding

MAPE and RMSE values of 23.954% and 3.31%, respectively. In future investigations, alternative inputs such as moving averages and standard deviations of closing stock prices may be incorporated to potentially enhance predictive accuracy.

## References

- [1] Soni P, Yogya T, et al. Machine Learning approaches in stock price prediction: A systematic review. *Journal of Physics: Conference Series*, 2022, 2161 (1): 012065.
- [2] Gandhmal D P, Kumar K. Systematic analysis and review of stock market prediction techniques. *Computer Science Review*, 2019, 34: 100190.
- [3] Al-Tamimi H A H, Alwan A A, Abdel Rahman A A. Factors affecting stock prices in the UAE financial markets. *Journal of transnational management*, 2011, 16 (1): 3 - 19.
- [4] Huang J, Chai J, Cho S. Deep learning in finance and banking: A literature review and classification. *Frontiers of Business Research in China*, 2020, 14 (1): 1 - 24.
- [5] Qiu Y, Wang J, Jin Z, et al. Pose-guided matching based on deep learning for assessing quality of action on rehabilitation training. *Biomedical Signal Processing and Control*, 2022, 72: 103323.
- [6] Cavalcante R C, Brasileiro R C, Souza V L, et al. Computational intelligence and financial markets: A survey and future directions. *Expert Systems with Applications*, 2016, 55: 194 - 211.
- [7] Guo T, Xu Z, Yao X, et al. Robust online time series prediction with recurrent neural networks. 2016 IEEE international conference on data science and advanced analytics (DSAA). *Ieee*, 2016: 816 - 825.
- [8] Sherstinsky A. Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. *Physica D: Nonlinear Phenomena*, 2020, 404, 132306.
- [9] Sunny M A I, Maswood M M S, Alharbi A G. Deep learning-based stock price prediction using LSTM and bi-directional LSTM model. 2020 2nd novel intelligent and leading emerging sciences conference (NILES). *IEEE*, 2020: 87 - 92.
- [10] Roondiwala M, Patel H, Varma S. Predicting stock prices using LSTM. *International Journal of Science and Research (IJSR)*, 2017, 6 (4): 1754 - 1756.
- [11] Han C, Fu X. Challenge and opportunity: deep learning-based stock price prediction by using Bi-directional LSTM model. *Frontiers in Business, Economics and Management*, 2023, 8 (2): 51 - 54.
- [12] Kaggle - TESLA Stock Data, <<https://www.kaggle.com/datasets/varpit94/tesla-stock-data-updated-till-28jun2021>> (Accessed on November 2, 2023).