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Analysis of stock forecasting based on LSTM

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Abstract. The use of the long short-term memory (LSTM) machine learning algorithm for stock prediction is widely used contemporarily. This study the feasibility of price prediction based on LSTM. This study first collected extensive data on stock prices, including the closing prices, volumes, and other relevant indicators, for several companies. Then, it implemented an LSTM-based model using this data, which was trained on a dataset containing historical stock price information over a fixed period. The model's performance was evaluated using a separate test set. Based on the analysis, LSTM is successful in forecasting stock a remarkable degree of precision, rendering it an invaluable asset for investors aiming to make well-informed investment choices. Its ability to capture long-term dependencies and patterns within time series data makes it an ideal choice for forecasting future trends in financial markets. By leveraging this model, investors can gain valuable insights into potential market movements and adjust their investment strategies accordingly. Overall, the promising results obtained from applying LSTM-based models highlight their potential value in supporting investors' decision-making processes and ultimately improving investment outcomes.

Keywords: Machine learning, stock prediction, LSTM.

1. Introduction

In recent years, the stock market has become an important component of the global economy, with millions of investors participating in this complex market daily [1]. With the development of machine learning technology, more and more researchers are applying machine learning algorithms to stock prediction, hoping to discover the rules and patterns of stock price movements through data analysis. This study investigates the use of long short-term memory (LSTM) machine learning algorithm for stock prediction [2], which is one of the most promising approaches in this field. LSTM is a type of recurrent neural network (RNN) that can effectively capture sequential dependencies in data and has been widely used in various time-series prediction tasks [3]. This study aims to explore the potential of LSTM in predicting stock prices by analysing historical stock price data. It is found that SVM [4], LSTM and Random Forest are three most common method to build the model of Stock Price Prediction. By comparison, LSTM and Random Forest are more stable in practical applications [5], although they train for a longer time. At present, LSTM and other improved variants of RNN will be more popular in the general environment. In addition, the combination of algorithms and hybrid models are also very good choices. This study chose LSTM as majority of the algorithm. Then, during the implementation, some problems began to emerge like noise in stock price data, stock prices' own non-stationarity and data scarcity. It is decided to use dropout to prevent LSTM models from memorizing noise in the training data. The study also prevents overfitting by using a dropout function [6], where the authors randomly drop a subset of neural network units during training, only temporarily removing the training process. Finally, a good prediction result is obtained. However, although machine learning has many advantages in stock prediction, it also has its limitations. For example, it may not be able to handle sudden and unexpected events, while the effect may not be ideal for some complex and nonlinear data distributions. Therefore, in practice, it is necessary to combine other methods and tools to obtain more comprehensive and accurate prediction results.

2. Data and method

Based on the current study, SVM, LSTM and Random Forest are three most common method to build the model of Stock Price Prediction. By comparison, LSTM and Random Forest are more stable in practical applications, although they train for a longer time. At present, LSTM and other improved variants of RNN will be more popular in the general environment. In addition, the combination of algorithms and hybrid models are also very good choices. Therefore, this study chooses LSTM as majority of the algorithm. Then, during the implementation, some problems began to emerge like noise in stock price data, stock prices' own non-stationarity and data scarcity. Through the discussion, auther decided to use dropout to add dropout to prevent LSTM models from memorizing noise in the training data. And auther choose data from Amazon(2023.2~2023.8)and Tesla(2022.8~2023.8) as the final training data.

Dropout function [6].The dropout technique involves randomly deactivating a subset of neural network units during training, temporarily excluding them from the learning process. In other words, while propagating forward, there is a certain probability that the activation value of a neuron will be ignored. This approach promotes generalization in the model by reducing reliance on specific local features. It can be thought of as probabilistically lowering the quantity of active neural networks throughout training, reducing computational load and accelerating training. A frequent issue when training neural networks is overfitting. It happens when a model works effectively with low loss and high prediction accuracy on training data but shows more loss and worse prediction accuracy on test data.Dropout effectively mitigates overfitting by preventing excessive dependence on particular features during learning.

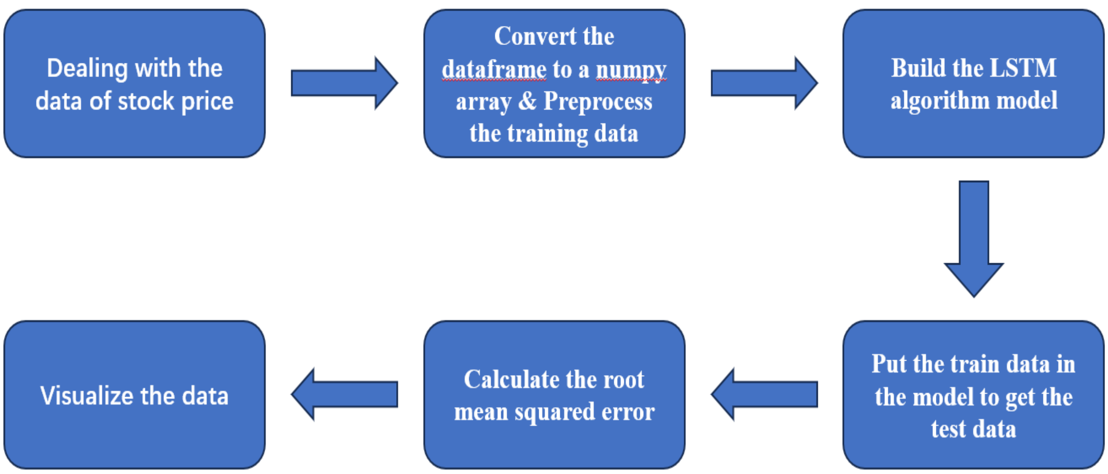

Figure 1. Stock Forecasting process (Photo/Picture credit: Original).

The current task is using python to implement the prediction by LSTM [6]. The process is shown in Fig. 1. Numpy (Numerical Python) is the most important basic package for numerical computation in Python. Most computing packages provide Numpy scientific functions that use Numpy arrays as a common language for data exchange. Numpy array provides convenient arithmetic operations based on array and broadcast mechanism, not only for fast matrix calculation of data, but also for reading and writing operations of array data in hard disk, providing efficient multi-dimensional array [7-10]. The first step is dealing with the data of the stock. The data provided by project is very simple, thus, need to use stock data on the web to add enough train data by the name of every stock(This data can be found on yahoo finance). Then convert the dataframe to a numpy array and preprocess the training data using MinMaxScaler. A particular kind of RNN is the LSTM algorithm, which stands for long short-term memory. The figure presented below shows the model's structure. In contrast to RNN, LSTM's output has a second pathway known as the cell state that runs the length of the entire network. It is noteworthy that this cell state pathway only comprises of multiplication and addition operations and lacks any nonlinear units. This unique characteristic allows for minimal modifications when passing the cell state to subsequent cells. The inclusion of different gates, including input, forget, and output gates, is the main feature of LSTM. These gates alter the weightage of self both the amount of information transmitted from previous cells (sigmoid outputs ranging from 0 to 1) and determining which information should be added to the cell state before being passed on to subsequent cells. Advantages of LSTM for stock price prediction are listed as follows:

- Temporal Dependencies. LSTMs can capture temporal dependencies in stock price data, recognizing patterns that traditional models might miss.
- Long-Term Patterns. LSTMs are adept at learning and retaining long-term trends, making them suitable for stock markets characterized by both short-term volatility and prolonged trends.
- Handling Non-linearity. Stock price movements often exhibit nonlinear behavior, and LSTMs are capable of capturing these intricate nonlinear relationships.
- Feature Learning. LSTMs can learn essential features automatically from raw price data, eliminating the need for manual feature engineering.

Continue by dividing the cleaned data into two arrays, x_train and y_train, and altering their form so that the LSTM model can use them. After processing the data, it is time to start building the LSTM algorithm model. Then put the train data in the model to get the test data which include x_test and y_test. The prediction can be obtained by x_test. The the root mean squared error can also be calculated by y_test and prediction result in the process of building model, the way of dropout was added.

3. Results and discussion

In the project, the stock data of Amazon was applied. After processing the above code as shown in Fig. 2. However, the model of this study still has potential for improvement. In the process of building model, the way of dropout was added (seen from Fig. 3). It can be found that the line of prediction become smoother than before, which means the influence of noise was decreased [8]. Then, this study added Tesla data and get similar results as given in Fig. 4.

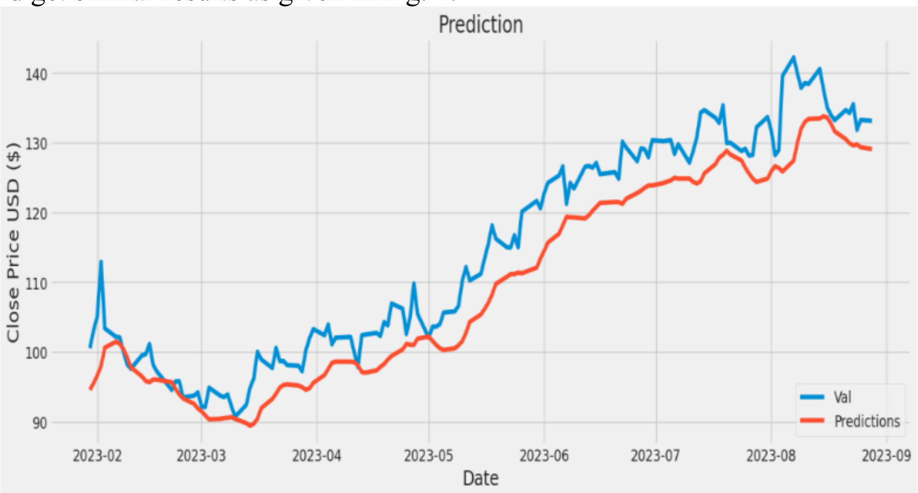

Figure 2. Amazon stock forecast results (Photo/Picture credit: Original).

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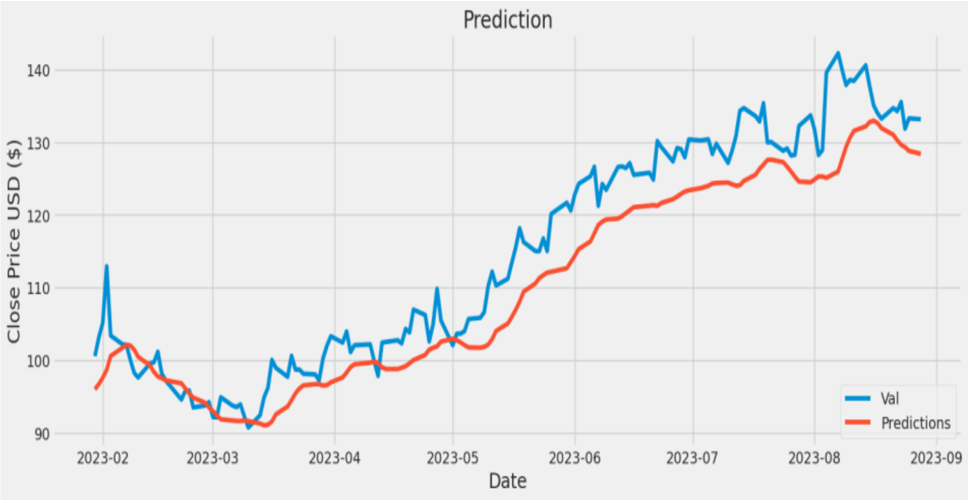

Figure 3. The new prediction (Photo/Picture credit: Original).

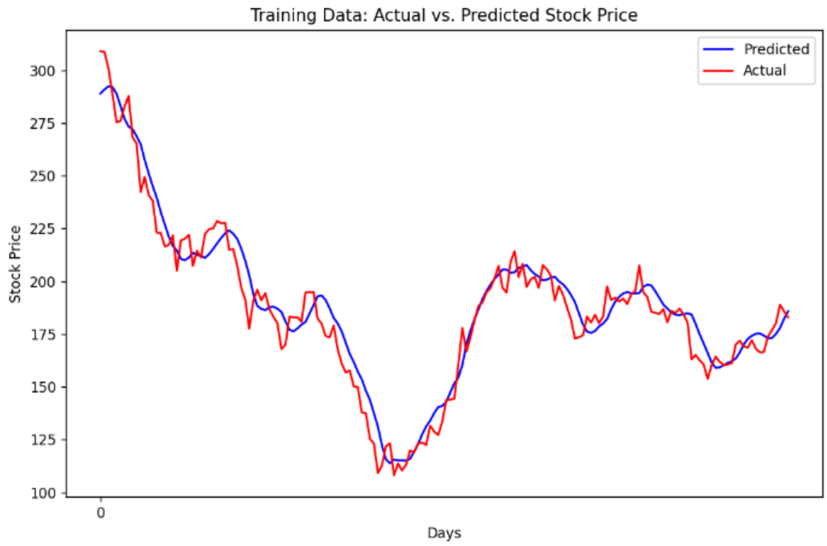

Figure 4. The predicted Tesla actual stock vs. forecast results (Photo/Picture credit: Original).

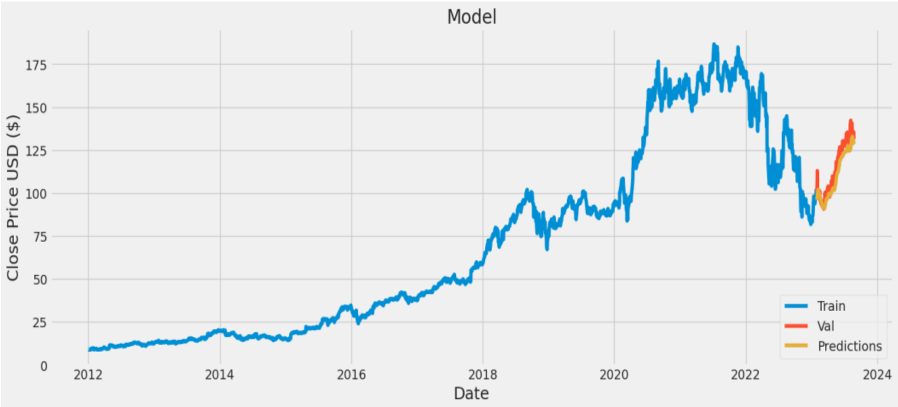

Figure 5. The difference between the predicted result and the actual stock (Photo/Picture credit: Original).

The degree of contact ratio between the anticipated value (predictions) and the actual value is quite high, as can be seen from Fig. 5. It is clear that the created model has some degree of viability. When break down the data into months, one finds that there are still gaps(the residual in regression analysis) in price predictions. It is found that the predicted value was generally lower than the true value. Although it is difficult to predict a sharp rise and fall in price, this model still has great reference value (as given in Fig. 6). Seen from Fig. 7, this image's distinction from the previous one is a lessened impact of noise. It is found that the gaps between the actual values and predicted values are reduced in some intervals. Moreover, the image becomes smoother. It is obvious that the elimination of noise makes the consistency of the predicted values even better.

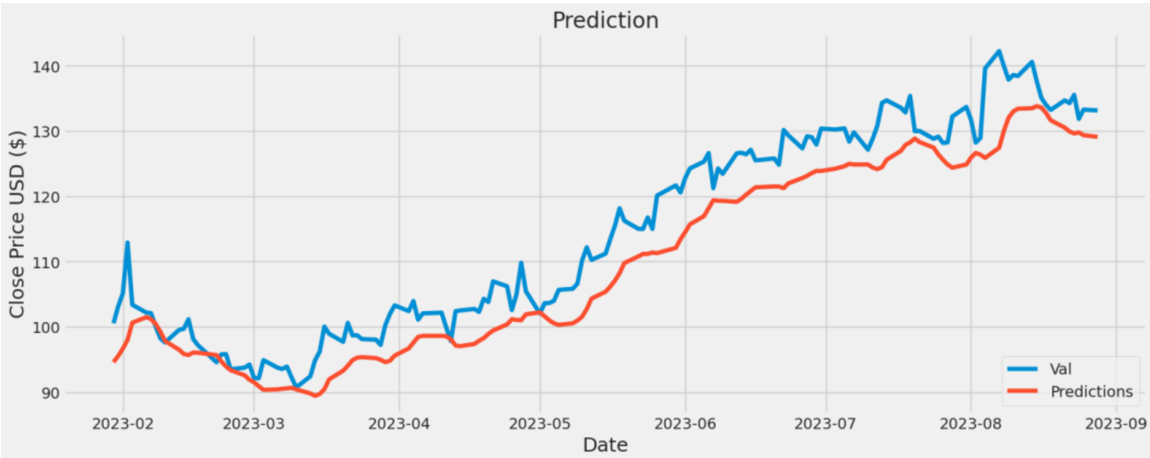

Figure 6. Forecast results and actual results on a monthly basis (Photo/Picture credit: Original).

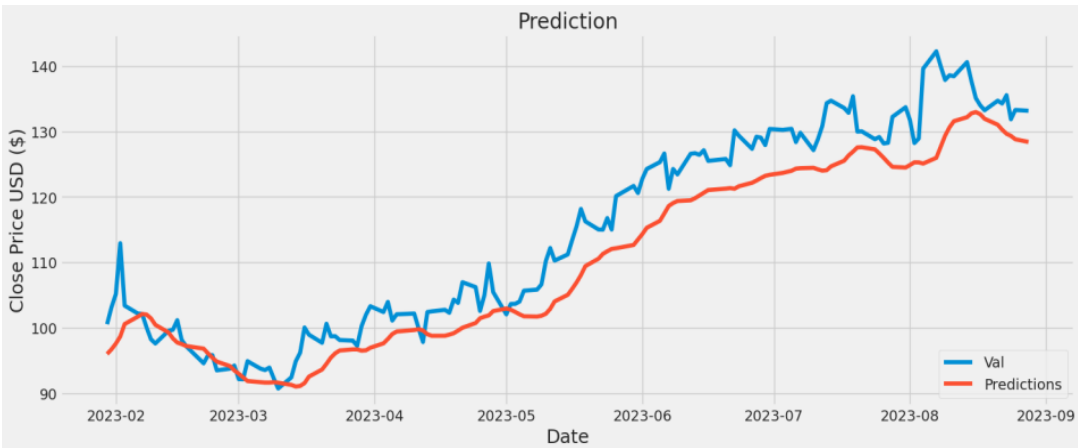

Figure 7. Reduced noise after prediction results with actual (Photo/Picture credit: Original).

4. Conclusion

To sum up, this study demonstrates how to forecast stock prices using machine learning with long short-term memory (LSTM). Using a dataset with historical stock price data and a comparison to the actual stock prices, this study analyzed the performance of the technique. The experimental findings show that the suggested method can anticipate stocks with high levels of accuracy and is useful for this purpose. For investors looking to make wise investment decisions, the LSTM-based model utilized in the author's work has demonstrated potential in stock price forecasting. As mentioned that predictive models based on hybrid deep learning are currently the mainstream research direction. According to the analysis, it is found that this type of technology has achieved remarkable results in the recent past, and selected two methods to discuss the future improvement of stock prediction. In order to ensure precise and quick results, the initial method is on advising a combined predictive model for stock price prediction that includes a one-dimensional Convolutional Neural Network (CNN) and a Bidirectional Cuda Deep Neural Network Long Short-Term Memory [9].

The second method in this sector makes use of deep learning techniques, whose performance has lately eclipsed that of conventional machine learning approaches. the GRU-based StockNet model adds two modules as part of a fresh data augmentation strategy to alleviate overfitting issues. This study combines an injection module and an investigation module created expressly for predicting stock index changes to address overfitting concerns. the suggested methodology has been successfully validated using the CNX-Nifty index of the Indian stock market.

The use of machine learning for stock forecasting is likely to become even more widespread in the future. This technique can be used to analyse historical data, identify market trends, predicting stock price changes and evaluating stock risk. These functions are very useful for investors because they can make their investment strategies based on these prediction results. Specifically, machine learning algorithms can be applied to

- Trend prediction. By analysing the historical data, the algorithm can predict the future trend of the stock price, offer the decision basis for investors.
- Risk Assessment. Machine learning can assess the risk of stocks and help investors avoid investing in risky stocks.
- Anomaly detection. The algorithm can detect abnormal behaviour in stock trading, such as abnormal price fluctuations, so that investors can take countermeasures in time.
- Real-time prediction. machine learning can be real time analysis of stock data, provide real-time prediction results, enable investors to adjust investment strategy.
- Complex dataset analysis. For datasets containing large amounts of data and complex relationships, machine learning algorithms can effectively extract key information to provide more accurate and comprehensive decision support for investors.

However, should also be noted that although machine learning in the stock prediction has many advantages, but also has its limitations. For example, it may not be able to deal with sudden and unexpected event, and for some complex, nonlinear data distribution, the effect may not be ideal. In practice, therefore, need to combined with other methods and tools, to obtain a more comprehensive, more accurate prediction results.

References

[1] Argade S, Chothe P, Gawande A and Joshi S 2022 SSRN 4128716.
[2] Mobarra M 2023 LSTM stock price prediction Kaggle Retrieved from: https://wwwkagglecom/code/mahdimobarra/lstm-stock-price-prediction.
[3] Colah A 2015 Understanding LSTM networks Retrieved from: http://colahgithubio/posts/2015-08-Understanding-LSTMs/
[4] Grigoryan H 2016 Database Systems Journal vol 7 p 1.
[5] Qian F and Chen X 2019 IEEE 4th International Conference on Cloud Computing and Big Data Analysis (ICCCBDA) Chengdu China 2019 pp 483-486.
[6] Cheng L C, Huang Y H, and Wu M E 2018 IEEE International Conference on Big Data (Big Data) Seattle WA USA pp 4716-4718.
[7] Tinto V 1975 Review of Educational Research vol 45(1) pp 89-125.
[8] Madge S and Bhatt S 2015 Applied Mathematics Journal of Hindawi vol 20 p 18.
[9] Gupta U Bhattacharjee V and Bishnu P S 2022 Expert Systems with Applications vol 207 p 117986.
[10] Kanwal A, Lau M F, Ng S P H, Sim K Y and Chandrasekaran S 2022 Expert Systems with Applications vol 202 p 117123.