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Research on Stock Price Prediction by LSTM

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Abstract:

The stock market's influence on the contemporary economy is profound, with its fluctuations directing the investment strategies of traders and investors. The intricacies and volatility of the market have consistently drawn the interest of data scientists. Forecasting stock prices is a complex task, influenced by various factors, ranging from individual company financials to global economic indicators. The effectiveness of Long Short-Term Memory (LSTM) models in predicting stock prices has been demonstrated in multiple studies and practical applications. They can capture non-linear trends and seasonal patterns in stock price movements, providing valuable insights for investors and traders. For those interested in implementing LSTM models for stock price prediction, numerous resources are available, including tutorials, research papers, and platforms that offer pre-trained models or APIs for financial forecasting. This study aims to develop a deep learning framework using LSTM networks to identify underlying trends within the data. The objective is to predict future stock market price movements by leveraging LSTM's ability to model time series data effectively. By tapping into the predictive power of LSTM, this model can seek to provide investors with a sophisticated tool for making well-informed investment decisions, enhancing the precision of stock price predictions.

Keywords: Stock price prediction; LSTM; Time series data.

1. Introduction

Stocks can be freely traded by investors on the stock market. The stock market has a lengthy history and serves as a means for companies to raise capital [1]. Selling stocks allows an enormous amount of money to flow into the stock market, changing the composition of company capital and accelerating the growth of the market economy.

One of the things that concerns stock market investors the most is the pattern of price fluctuations [2]. Stock price fluctuations are impacted by a wide range of factors, including shifts in the global economic landscape, global conditions, and domestic policies [3]. As a result, stock price fluctuations are unpredictable and nonlinear, and forecasting stock price

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fluctuations has long been a crucial topic of study for economists [4]. Investor risk can be drastically reduced by making accurate stock price predictions. Moreover, accurate forecasting may significantly aid investors in boosting their investment returns.

However, it is challenging to glean valuable data from historical swings because of the volatility and non-linearity of movements in the stock market. In the past, several academics suggested techniques for stock price prediction, such as processing time series data and intricate nonlinear interactions applying deep learning algorithms and networks of neurones. These days, conventional machine learning techniques, ARIMA, and linear regression techniques are used by academics to forecast stock prices [5]. These techniques do have a drawback, though, in that they are not accurate enough to forecast noticeable changes in price.

This study suggests an LSTM-based technique for predicting the stock price for the following day in order to more precisely forecast stock price variations. This technique can build an LSTM model, compile and train it, and produce both a training dataset and a scaled training dataset. An optimization of RNN networks called LSTM can prevent some of the gradient issues brought on by RNN. The effect of historical time series data states on stock prices may also be obtained.

It should be noted that rather than forecasting future stock price data based on current data, the predictions in this article are based on developing a model employing previous data to compute and anticipate existing data, as well as to show the error between it and the actual existing data. due to the former's inability to confirm the model's true efficacy. The latter can show off the model's predicted accuracy in an intuitive way.

2. Literature Review

In general, stock price predictions are made using mathematical models [6]. Initially, data scientists processed stock data using basic linear models such as regression models [7]. However, due to the inclusion of numerous unknown elements and interference terms in stock data, such as business news, industry performance, and attitudes, as indicated in [8], the constraints of linear models become more severe as forecast time grows [9]. Nowadays, scientists at home and abroad have explored a variety of strategies and models for forecasting stock values, including vector autoregression models, error correction models, and Bayesian vector autoregression models [6].

Nonlinear models are becoming more and more popular among data scientists, who have also effectively used machine learning techniques like neural networks to forecast market values [2,10]. Therefore, machine learning techniques have been a major influence on stock prediction [11]. Numerous studies' findings have demonstrated that LSTM outperforms other prediction models in terms of accuracy when used as a learning model for stock price prediction [12]. Thus, the field of stock prediction has greatly benefited from machine learning techniques [11,13]. Nonetheless, a number of experimental findings suggest brain networks.

A 2019 study on the application of BiLSTM to S&P 500 index prediction revealed that, compared to other prediction models, LSTM prediction of stock prices produces more accurate results [12].

3. Methodology

3.1 Brief understanding of LSTM

The LSTM is a unique kind of RNN, which was introduced in 1997 by Hochreiter and Schmidhuber. It is intended to address the issue of long-term reliance that ordinary RNNs run into when handling data with a long sequence. In domains including language modelling, speech recognition, and time series analysis, LSTM excels, particularly when it comes to jobs requiring long-term retention of data.

3.2 Key features of LSTM

Gate control mechanism: The LSTM provides three types of gate control mechanisms that may govern the flow of information: input gate, forget gate, and output gate.

Cell State: The LSTM includes a Cell State, which functions as a conveyor belt and may transport information between time steps. The cellular state contributes to long-term memory retention.

Input gate: decides which fresh data should be stored in the cellular state. It generally consists of a sigmoid layer to calculate the number of updates and a tanh layer to generate new candidate value.

Forgotten Gate: Deciding whether to reject or keep certain knowledge. It is accomplished by a sigmoid activation function that generates a value between 0 and one, reflecting the degree of knowledge retention.

Output gate: decides what information will be included in the next concealed state. It employs a sigmoid layer to select which part of the cell state can be output, and a tanh layer to standardise the output values.

Parameter sharing: In LSTM, parameters from the same layer are shared at all time steps, which helps minimise the complexity and computational cost of the model.

3.3 The workflow of LSTM:

Based on the current input and the prior concealed state, Forgotten Gate determines which data should be forgotten. The new information that can be contributed to the cell state is calculated by input gates and updates. Update the cell state by combining the outputs of the input and forget gates. Based on the updated cell state and the current input, the output gate determines the output value. Until the sequence is finished, loop back through the previous steps at each time step. The display result is shown in Fig. 1.

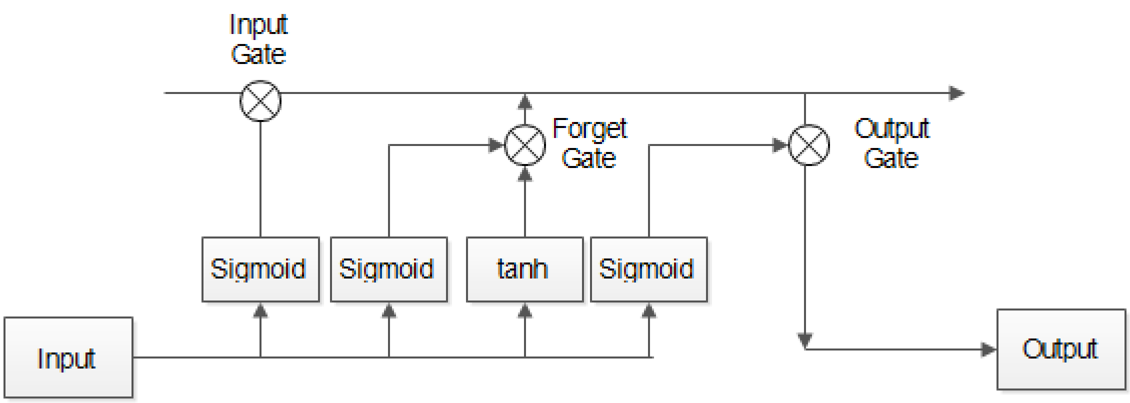

Fig. 1 Architecture of LSTM memory cell

It is depicted in Fig. 1 that Input, Forget and Output gates are deployed in LSTM. The input gate filters the information from previous layers and the output gate filters the output that is to be sent to the next layer. The cell state in LSTM is

$$Ct = Ft * C_{t-1} + It * \bar{C}_t \tag{1}$$

Where C_t is the current cell state and C_{t-1} is the previous cell state. F_t is the forgotten state and I_t is the Input state [6].

4. Result

The corporate stock price data used by the LSTM prediction model in this article is sourced from the Yahoo Finance website, which provides a threaded and Pythonic method for downloading market data from Yahoo. Data from the Open High Low Close Adj Close Volume are included in this. Table 1 is Several Data on the Market.

Table 1. Several data of market

Date	Open	High	Low	Close	Adj Close	Volume	Company name
2024-08-23	177.3400	178.9700	175.2400	177.0400	177.0400	29150100	AMAZON
2024-08-26	176.7000	177.4700	174.3000	175.5000	175.5000	22366200	AMAZON
2024-08-27	174.1500	174.8900	172.2500	173.1200	173.1200	29842000	AMAZON
2024-08-28	173.6900	173.6900	168.9200	170.8000	170.8000	29045000	AMAZON
2024-08-29	172.2200	1704.2900	170.8100	172.1200	172.1200	26407800	AMAZON
2024-08-30	172.7800	178.9000	172.6000	178.5000	178.5000	43429400	AMAZON
2024-09-03	177.5500	178.2600	175.2600	176.2500	176.2500	37735500	AMAZON

After obtaining the data foundation required for prediction, this study uses the. Script () function to construct an image function that displays the overall statistical data and analyzes numerical and object sequences. It can display a panoramic view of statistics and summarize the distribution shape and central tendency of the dataset. Table 2 is

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some view of statistics.

Table 2. Panoramic view of statistics

	Open	High	Low	Close	Adj Close	Volume
Count	251.0000	251.0000	251.0000	251.0000	251.0000	2.510000e+02
Mean	191.0129	192.7842	189.3838	191.1436	190.6378	5.948180e+07
Std	18.8756	19.1202	18.4478	18.7969	18.9710	2.490228e+07
Min	165.3500	166.4000	164.0800	165.0000	164.5860	2.404830e+07
25%	175.5450	177.3950	173.9200	175.6150	174.7530	4.592600e+07
50%	187.1500	188.4400	185.8400	187.1500	186.6804	5.337730e+07
75%	196.9000	198.2000	195.3800	197.7650	197.0174	6.563785e+07
100%	236.4800	237.2300	233.0900	234.8200	234.5485	2.464214e+08

The project use Info () to print information about the DataFrame, including the type of indexed data. Next, the model outputs a chart of the closing price and sales volume through code to demonstrate their relationship with the timeline. Figure 2 and Figure 3 are Closing price and Sales volume fluctuations.

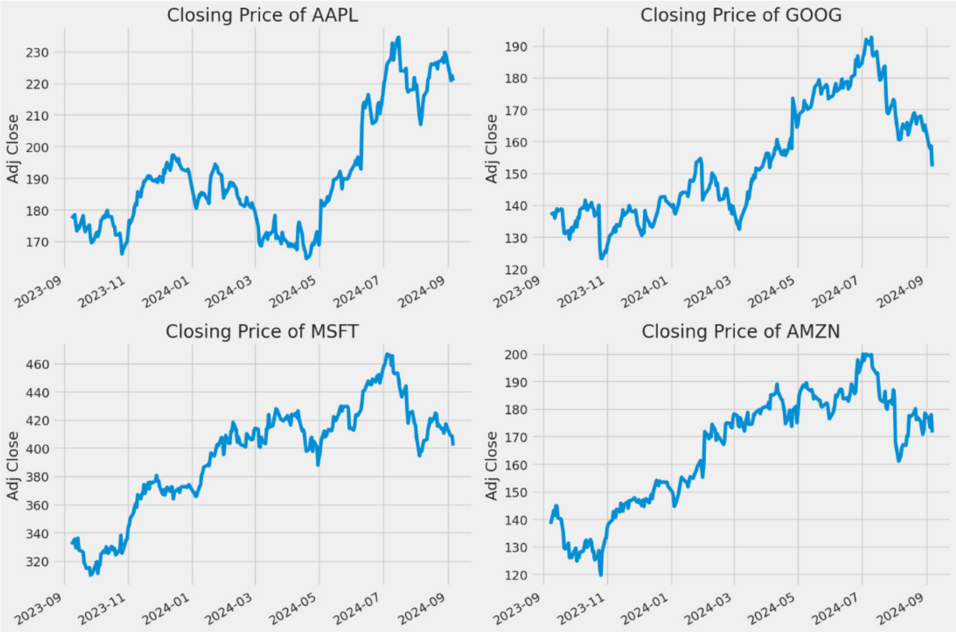

Fig. 2 Closing price

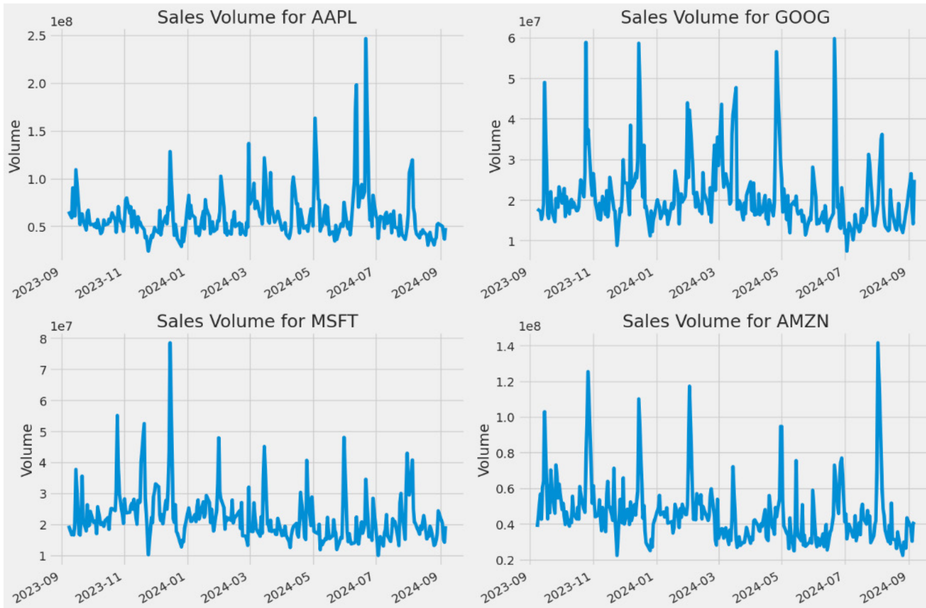

Fig. 3 Sales volume

Then model smooths the price data by analyzing the moving average of the stock. By retrieving the daily returns of past stocks, a histogram is obtained to determine which stock has the lowest risk for investors to purchase. Fig. 4 and Fig. 5 are the closing prices and daily returns of four companies.

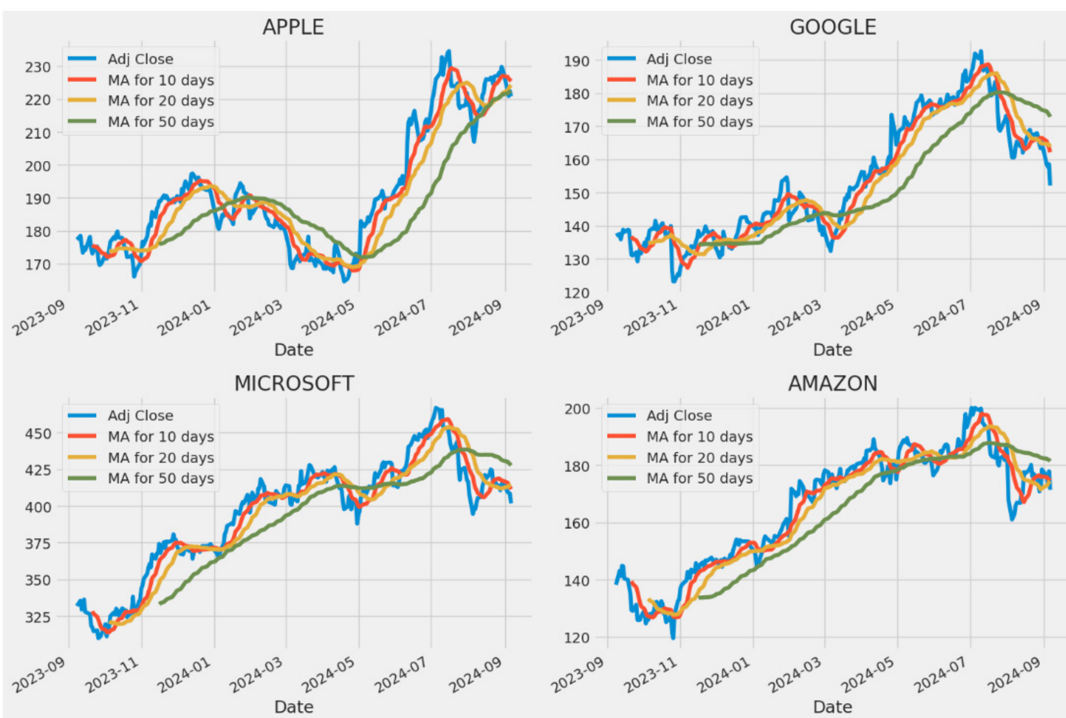

Fig. 4 Closing price with moving average

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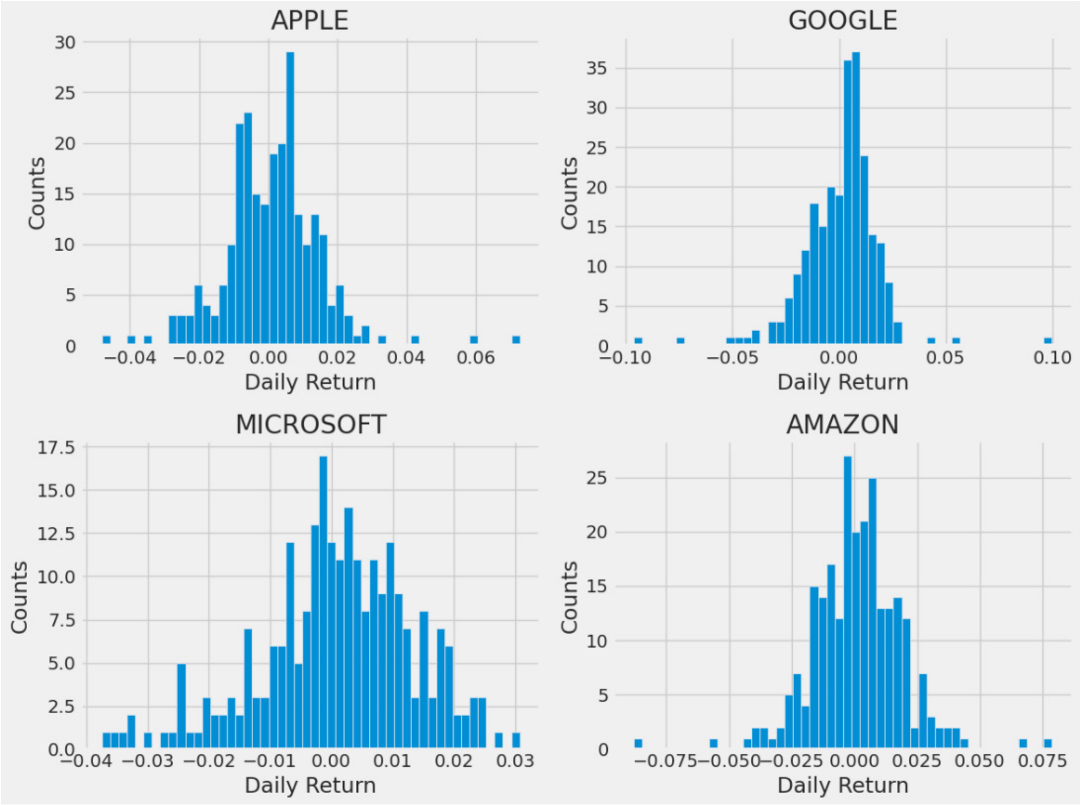

Fig. 5 Daily return

Finally, by obtaining stock quotes, a new data frame can be obtained, which can be converted into a NumPy array and scaled to output a data array. Next, create a training dataset and a scaled training dataset, split and transform them into NumPy arrays, and reshape them to output a new array. By constructing an LSTM model and compiling and training it, a trained model can be obtained. Create another test dataset to obtain the predicted price value and its root mean square error of the model. Converting it into a visual chart output enables the prediction of stock market prices. Fig. 6 is the line chart of predictions and Table 3 is the data format to intuitively display the error between the close and predictions.

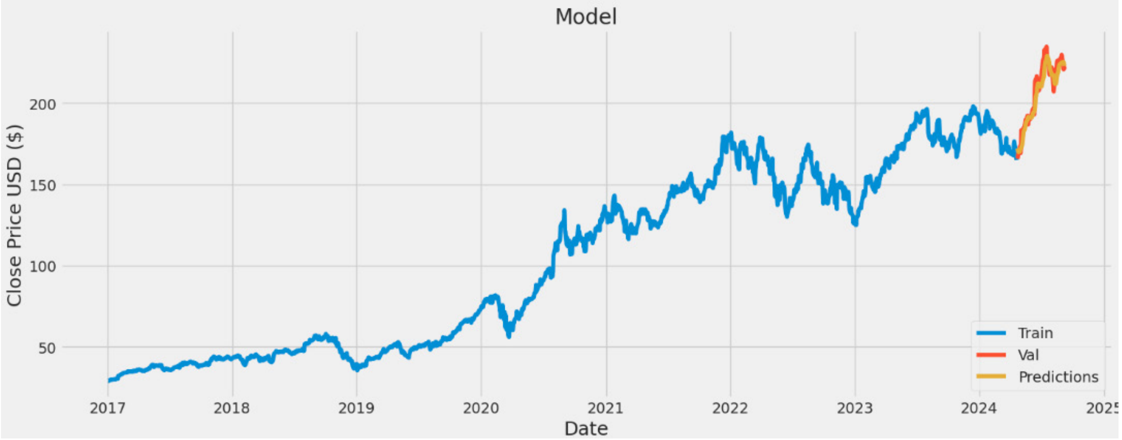

Fig. 6 Line chart of predictions

Table 3. Forecast table

Date	Close	Predictions
2024-04-22	165.839996	172.186584
2024-04-23	166.899994	171.074387
2024-04-24	169.020004	170.240662
…	…	…
2024-09-04	220.850006	225.038452
2024-09-05	222.380005	223.996124
2024-09-06	220.820007	222.951736

Based on the above experimental results, it can be found that the error between stock price analysis and prediction using LSTM architecture and the true value is relatively small, while according to [13], It can be also observed that the accuracy of LSTM predictions has indeed increased significantly compared to existing prediction models. Therefore, the LSTM model for predicting stock prices this time is successful, as it accurately predicts the possible fluctuations in stock prices over time and maintains them within a relatively small error range.

5. Conclusion

This article suggests a technique for building an LSTM model to forecast the closing price of stocks based on the pattern of price fluctuations. The opening price, highest price, lowest price, adjusted close price, and volume are all collected by this model. It then learns and extracts characteristics from the input data in order to forecast future changes in the closing price. The experimental findings demonstrate that it is less impacted by significant swings in stock prices and has extremely good forecast accuracy, with an error range of no more than 7. As a result, LSTM is an excellent method for stock price prediction.

The future research goal can be to adjust some of the code in the model and attempt to use the BiLSTM model to make the results more accurate. And try to extend this to predict natural aspects such as weather and earthquakes.

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