Long Short-term Memory Neural Network Model for Stock Prediction under COVID-19 Pandemic

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Abstract—Due to disasters like the COVID-19 pandemic, the stock markets became more volatile than before. To avoid significant losses, it is important for investors to accurately predict big variations in stock prices under the impact of the pandemic through financial modeling. In this paper, an advanced model, the Long Short-term Memory Model (LSTM) was introduced, which makes a more accurate prediction than the previous technical-based models (e.g. ARIMA) under the current circumstance. The study implemented the daily stock price from three technological firms. The dataset was divided into two parts. One was used for training and optimizing the model, while the other was for testing the accuracy of the model. With the training dataset, the model began memorizing the important features within the sequential data, which are shown as the updating cell state and hidden state within the model. After the optimization, it generated the predicted value using the testing dataset and compared it with the real value to present its accuracy. Experimental results indicated that the LSTM model achieved the purpose of forecasting every significant variation in stock price trends, although the trends are unstable under the influence of the pandemic.

Keywords-Stock price prediction; LSTM Model; Pandemic.

1 INTRODUCTION

The stock market is one of the most essential parts of a country, which aims to promote the investment and growth of global firms. Stock price prediction becomes crucial for both institutions and individuals to earn as much profit as possible. However, many factors would influence the stock price, such as government policy changes, inflation, and technological changes. All kinds of those factors would cause fluctuations in stock price over time, making a big difference in the gain or loss that the investors would get. Therefore, investors need to predict the variations of future stock prices, which will avoid significant losses and have more profits. To achieve more accuracy in prediction, financial modeling in stock price prediction is required.

To accurately forecast of future stock prices, various financial models are created by quantizing different types of risks that would affect stock prices. In the early field of stock price prediction, the modeling was mainly completed by using theoretical or technical linear models. It began with the Capital Asset Pricing Model (CAPM) using simple linear regression and the upcoming FAMA-French model including several factors such as Small Minus Big (SML) and High Minus Low (HML). Based on the term plots and diagnostic plots studied in [1], those previous models suffered violations of constant variance and linearity for all stocks. To reduce the involvement of statistical assumptions, the modeling then turned out to be more technical based. Models like

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ARMA and ARIMA were created, which used autocorrelation and time series to estimate the future stock price. The implementation of the ARIMA model in [2] shows that the ARIMA model could only be implemented after eliminating the instability of time series data. However, methods assuming the stability of data for forecasting are no longer suitable when the COVID-19 pandemic happened at the beginning of 2020.

With the pandemic's impact on various financial risks (e.g. credit risk, market risk), the stock price appeared to experience large fluctuations. For example, in this study [3], the author discussed its negative impact on the airline and hotel industry of America. It reported that hotels had lost more than $46 billion in revenue and the airlines have lost $419 billion so far in August 2020. This made the stock price not as stable as before. As a result, financial models which allow the instability in stock price data are needed for predicting the uncertainties in financial markets. Creating financial models that could take big variations in stock price into account becomes essential, which, however, requires more complication in modeling.

In this regard, this article recommends an artificial neural network for accurate stock price prediction since it has achieved many successes in other tasks [4-6], allowing the instability of stock prices. It is called the Long Short-term Memory Model (LSTM) [7]. It could generate the predicted value of a dataset by identifying the important parts in the sequence structure of the dataset and forgetting the less important ones of the dataset structure. With the proper implementation, it can be employed to generate the predicted stock price using the historical stock price dataset of firms in financial markets, even under the influence of the COVID-19 pandemic.

2 METHODLOGY

2.1 Data Description and Preprocessing

In this project, the dataset of the three computer software companies in the U.S. from Yahoo Finance was used [8]. The stock price trend from 2019 to 2022 is shown in Figure 1. To implement the LSTM model, this study specifically implemented the stock price of Zoom, Microsoft, and Alphabet Inc. (i.e. Google). The original dataset included the daily stock price of those firms from May 2019 to May 2022, which provided a sample size of 756 in total for each of the three firms. Figure 1 presents the stock price trends of the three companies, which indicate several fluctuations over time.

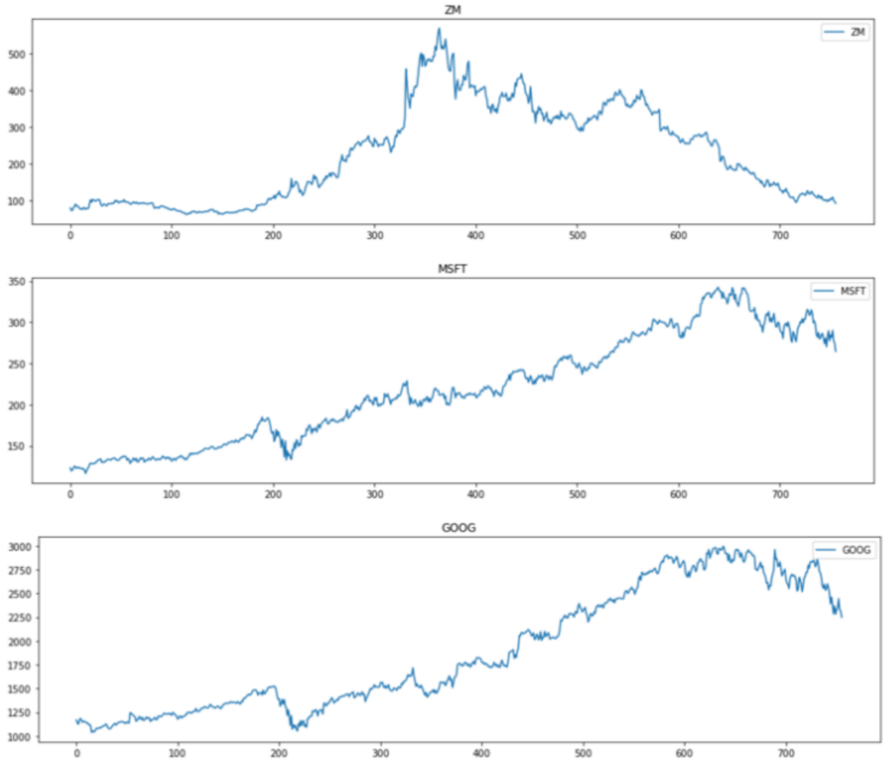

Figure 1. Daily Stock Price Trend of Zoom, Microsoft and Google.

For the preprocessing part, the study divided this dataset into two parts. The first 80% of data was referred to as the training dataset, while the rest of the 20% was regarded as the testing dataset. Both the train and testing datasets were then normalized using MinMaxScaler to speed up the training process. To first prove the feasibility and accuracy of the model, the training dataset was separated into x and y and compared the calculated y and the real y. In the 'cell' of the LSTM model, for the current predicted value (y), this study took the four values before the predicted value as the training dataset x, which is regarded as the one-time input (x_t) in the model.

2.2 LSTM Model Implementation

After having the inputs, this paper referred to the logic of the LSTM model to make the prediction. The model uses the concept of a cell, which consists of three main gates (also called layers), namely, the input gate, forget gate, and output gate. By putting the input (x_t) into the model, along with the updating cell state (c_t) and hidden state (h_t), the model identifies the important parts of the sequence structure and forgets the less important ones during the process. It then generates the current output (y_t) after breaching out the hidden state (h_t) [9]. The process is shown in Figure 2 [10]. When choosing time-series data (stock price for instance), the model turns out to be suitable for predicting the future value by simply implementing the regulated data over time.

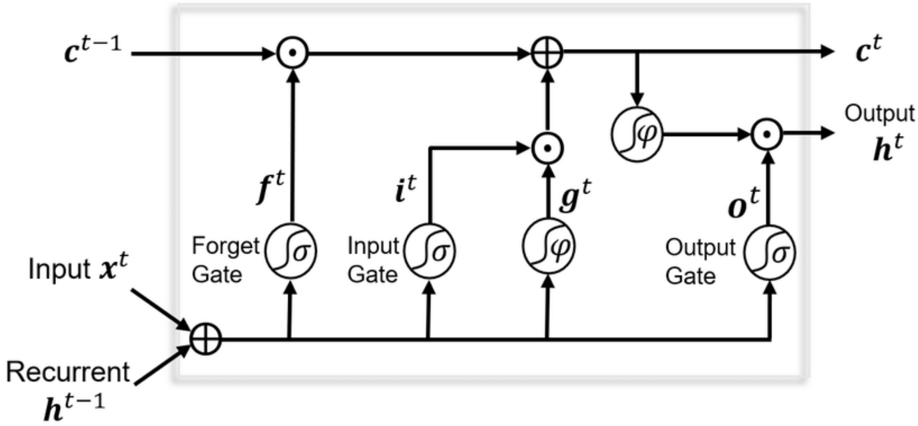

Figure 2. Visualization of a 'cell' in the LSTM model [10].

In this project, the study started by first creating an empty ‘cell’ using the way called Sequential in Keras, and then added the ‘gates’ in the cell. After putting the input (i.e. training dataset) into the model the study created, the output was then generated. The architecture for the LSTM model was shown in Table 1. From the table, it indicated the four layers. The two LSTM layers were used for collecting and processing time-series data. While Dropout was for excluding some cells to prevent overfitting, the last layer (i.e. Dense) was used for getting the output. The number of parameters in the model was 85, 671.

Table 1 The structure of the LSTM model.

LSTM Model Codes	**Model Properties**		
	Layer (type)	***Output Shape***	***Param #***
1	lstm_10 (LSTM)	(None, 4, 128)	66560
2	dropout_3 (Dropout)	(None, 4, 128)	0
3	lstm_11 (LSTM)	(None, 30)	19080
4	dense_5 (Dense)	(None, 1)	31

2.3 Hyperparameter Configuration

The predicted value from the training dataset was made. However, the difference between the output value of y and the real value of y still exists. As a result, to improve the accuracy of the model, this article used the SGD (i.e. Stochastic Gradient Descent) approach to optimize the calculation in the LSTM model. The study complied with the optimizer (i.e. root mean square propagation) and loss (referred to mean square error) of the data. The optimization process then had several times of training (i.e. epoch=50). By inputting the testing dataset (i.e. testing dataset) into the optimized LSTM model, the predicted results were then generated in the form of a normalized value. After renormalization, the article compared the predicted stock price trend and the real stock price trend through data visualization to observe the model's ability to accurately predict future values in practice.

3 RESULT AND DISCUSSION

3.1 Performance of models

Table 2 Calculated RMSE and MAE for Zoom, Microsoft, and Google stock

Error Types	COMPANY NAMES		
	Zoom	***Microsoft***	***Google***
RMSE	0.05268	0.10437	0.10643
MAE	0.04164	0.08644	0.08581

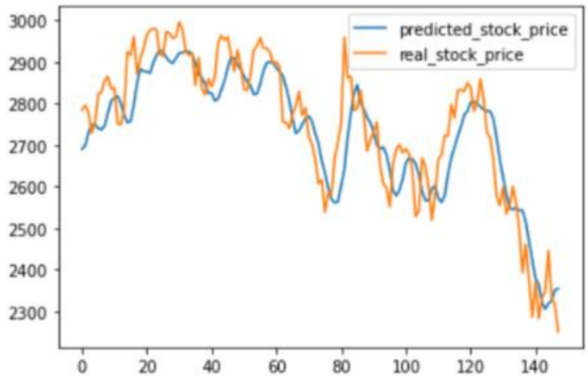

Figure 3. Visualization of stock price prediction for Google

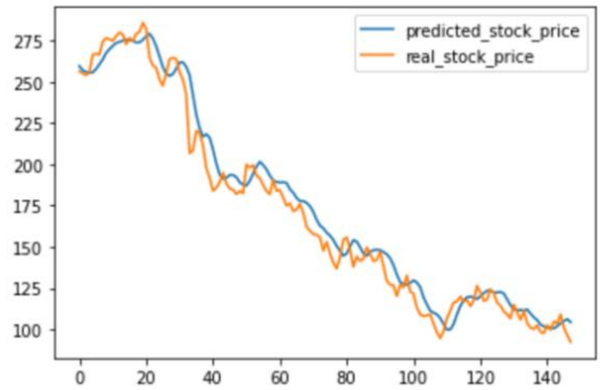

Figure 4. Visualization of stock price prediction for Zoom

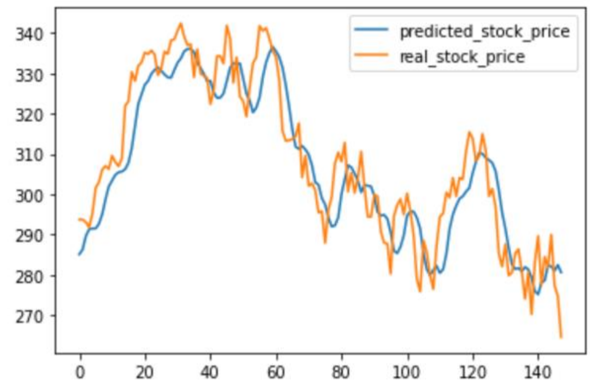

Figure 5. Visualization of stock price prediction for Microsoft

With the optimization, the error was minimized, which was presented in the form of Root Mean Square Error (i.e. RMSE) and Absolute Error (i.e. MAE) in Table II. In Figure 3, the study indicated that the time when the predicted variation of stock price appeared was the same as the time when the real fluctuation occurred for Google. The model correctly predicted a dramatic drop after the time of both 80 and 120 although the stock has experienced a significant rise before that time (i.e. time 80 and 120 days). Similar results were also made for the other two companies (i.e. Zoom and Microsoft), as shown in Figure 4 and Figure 5.

By matching the turning points of the predicted and the real curve, it was presented that the model accurately forecasted every one of the large fluctuations in the stock price trend, which is important for long-term investment. From Microsoft in Figure 6, since the model detected the future decline of stock after 2021 (i.e. 60 days on the x-axis), the investors could then make accurate investment decisions based on the predicted timing of the stock decline. Additionally, the small variations in each of the big fluctuations were also sophisticatedly forecasted, which makes the model also beneficial for medium or short-term investors. There is always uncertainty in financial markets, which would cause variability in firm stock prices. By using more parameters and having more layers than the standard neural network model, the LSTM model better helps both long-term and short-term investors to get significant gains instead of experiencing large losses by accurately forecasting the future stock price volatility. However, by observing the conflict between the predicted trend and the real trend after 140 days (i.e. 140 days on the x-axis in Figure 3, 5), the paper suggested that more improvements are required for predicting the stock trend that is in the further period as the historical dataset might not provide the model with sufficient important properties for more accurate prediction purposes.

In addition, although the model allows the instability of data, it appeared to operate better when the data is relatively more stable. The LSTM model perfectly predict the small variations in Figure 4, while the difference of the predicted value and the real value is bigger in Figure 3 and 5. The ability of forecasting the large variations of the LSTM model should also be improved in future studies.

4 CONCLUSION

In conclusion, this article helps the prediction of future stock prices to remain accurate under the effect of the pandemic by introducing financial modeling that allows the instability in time series data. The study specifically used the Long Short-term Memory Model to generate the predicted stock price, showing the possible variations in the future stock price trend. With the produced output, this study compared the predicted volatility and the real volatility in the stock price of three different firms. It was shown that the prediction perfectly matches the real stock price trend. It proved the accuracy of the LSTM model under the circumstance where the market became more volatile, and the stock price was more likely to be unstable over time. In the future, more improvements plan to be made to the model for more accurate prediction, particularly for predicting the stock price for a longer period.

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