Open Journal of Modelling and Simulation, 2022, 10, 428-440
https://www.scirp.org/journal/ojmsi
ISSN Online: 2327-4026
ISSN Print: 2327-4018

Prediction of the Technology Company's Stock Price through the Deep Learning Method

Meng Wang

University of Leeds, Leeds, UK
Email: wangmeng782019@163.com

How to cite this paper: Wang, M. (2022) Prediction of the Technology Company's Stock Price through the Deep Learning Method. *Open Journal of Modelling and Simulation*, **10**, 428-440.
https://doi.org/10.4236/ojmsi.2022.104024

Received: September 19, 2022
Accepted: October 21, 2022
Published: October 24, 2022

Copyright © 2022 by author(s) and Scientific Research Publishing Inc.
This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).
http://creativecommons.org/licenses/by/4.0/
Open Access

Abstract

This work aims to utilize deep learning methods CNN and LSTM to predict the adjusted close price of eight technical companies. The proposed model is a CNN-LSTM hybrid model, which combined CNN and LSTM layers in the model. It was compared with the single LSTM model and double LSTM model to evaluate its performance. The results showed the CNN-LSTM made a great prediction and can predict a more accurate value than the other two models, but it still can be improved to reduce overfitting problems.

Keywords

Deep Learning, CNN, LSTM, Stock Forecast

1. Introduction

The stock prediction has always been a challenging project as the stock market is a complicated, evolutionary and non-linear energetic market, which is influenced by numerous factors like government policy, economic environment, and the global market. The introduction of the Efficient Market Hypothesis (EMH) by Eugene Fama in 1970 laid the theory to support stock analysis. There are two types of stock analysis, fundamental analysis and technical analysis. Fundamental analysis evaluates a company's value by assessing its financial performance, business model and its economic environment, while technical analysis evaluates a stock's value through its past market data. Historical market data can reflect all relative information, and investors would repeat their investing action [1]. Hence, investors can realize the pattern of the stock market by analyzing their historical data.

Technical analysis of time series data has been researched for many years, various techniques can be used, for example, the Auto-regressive model, Moving average model, and Autoregressive integrated moving average (ARIMA). ARIMA is effective to analyze short-term non-stationary data. And machine learning is widely researched to analyze and predict stock market data such as the Black-Scholes Option pricing model (BSOPM), Support vector machines (SVM), and Random forest (RF). Artificial technology has been developed and leveraged to analyze and predict time series data as well. Deep learning methods such as Recurrent neural network (RNN) and Convolutional Neural Network (CNN) are popular for analyzing data. Further, Long-short Term Memory is one of the typical methods from RNN, which can overcome the gradient dispersion and long-range dependency problems of traditional RNN [2]. It also has great performance to predict time series data, whereas one-dimension convolution (Cov1D) can extract the sequential features of time series. Hence, this project will introduce a CNN-LSTM hybrid model and evaluate its predicting performance by comparing it with the single LSTM and double LSTM model.

Technical analysis is a method to predict the trending of stock price by assessing historical market data, particularly price and trending volume. It contrasts to the EMH which illustrates the stock market can't be predicted. Technical analysis originated from financial market information hundreds of years ago. It firstly appeared at the statement of the Dutch Business market by Joseph de la Vega's who was a marketer in Amsterdam 17th century. Then, Homma Munehisa invented a technical method using candlestick techniques, which is developed as a technical analysis tool in 18th century. Trend analysis and chart figure were considered are one of influential works at the start of technical analysis [3]. Until now, more and more technical methods and tools have been advanced, especially with the rapid development of intelligent analyzing methods.

Many predicting methods can forecast the trend of stock data in technical analysis areas such as the auto-regressive model and moving average model. Autoregressive integrated moving average (ARIMA) is a classic analysis model to predict time series data generated from ARMA model by adding integrated components, which is effective to analyze non-stational data. It differences the time series data many times to eliminate the stationary influences [4]. ARIMA can be utilized to forecast short-term stock data, which was proved in the prediction of the Nokia and Zenith Bank index [5].

Apart from the moving average model, Machine Learning (ML) is also popular to predict the stock return. ML and Deep Learning (DL) show a decent advantage over time series models [6]. [7] compared different ML algorithms such as the decision tree, ensemble learning, and neural network with the Black-Scholes Option pricing model (BSOPM). The conclusion shows that the machine learning approach performed better than BSOPM. Support vector machines (SVM) are widely used to research the fluctuation of stock price, which combined with KNN to forecast the trend of Chinese stock data in different time intervals [8]. And [9] utilized SVM to predict the movement of a subset of Dow Jones Industrial Average stocks and compared SVM with a single logistic algorithm. It illustrated that SVM came up with better accuracy as SVM can resist overfitting than other models. Machine learning also can be used to explore different kinds of information. [10] proposed random forest to extract the relationship between the stock return and the features of millions of tweets. [11] proposed the Artificial Neural Network (ANN) and Random Forest (RF) to predict the next closing price of five companies. They used RMSE and MAPE to evaluate the accuracy of ANN and RF models, which proved ANN had better performance than RF. ANN is a computing method inspired by the biological neural network of animal brains. To evaluate the technical indicator like simple moving average in the Turkish stock market, ANN was merged with Harmony Search (HS) and Genetic Algorithm (GA) to diminish the overfitting or underfitting problems of ANN. And HS with ANN models were thought as the main models in this research [12].

The popularity of deep learning is mainly because people can achieve abundant training data from digital media and easily get access to GPU-driven computing [13]. Deep learning also has a satisfactory calculation in forecasting the time-series data. The common Dl models in the prediction of time-series data involve Multi-layer Perceptron (MLP), RNN, and CNN, while RNN includes Long short-term memory (LSTM) and Gated Recurrent Units (GRU). [14] compared the performance of RNN, long short-term memory (LSTM), Bidirectional LSTM (BiLSTM), Gated Recurrent units (GRUs), and Variational AutoEncoder (VAE) when predicting the amounts of new confirmed and recovered cases of COVID-19 in six countries. The result illustrated deep learning had the potential in predicting the new COVID-10 cases in the short term, and VAE performed better than other algorithms. [15] provided a C-RNN model for Forex time series which combined deep-Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN) to enhance the forecasting precision of exchange rate. They chose nine major foreign exchange rates, which demonstrated the proposed model had a great predicting performance.

In banking and financial area, deep learning also provides many effective methods to analyze and forecast. [16] proposed a deep learning procedure to explore the related discussion about the original description, which was utilized to research financial risk-based news information. [17] researched the literature about the application of deep learning in banking and finance industry between 2004-2018, which show the prediction of stock market and trading was the most popular topics as 67% of researches they found were about the stock.

2. Methodology

This project aims to leverage a CNN-LSTM hybrid model to predict the adjusted close price of technology companies in the next trading day. Convolutional Neural Network (CNN) is a deep feedforward artificial neural network, which can be leveraged as an encoder in an encoder-decoder structure and can't support sequence input directly. On the contrary, one-dimension CNN can read sequence input and automatically learn significant features. Then, LSTM can explain these contents, which also can capture the dependence of time series and achieve satisfying prediction. Besides, to verify CNN-LSTM model accuracy, it will be compared with single LSTM and double LSTM model

Based previous literature, CNN-LSTM has the potential probabilities to forecast the stock series data, which is worth to research their application on the stock market prediction. Besides, most of researches are to evaluate the whole stock market, and it is rare that analysts explore the stock market in different industries since the stock features will vary from different industries. For instance, stocks in retailer industry always are considered low risk as they sell necessaries like food and clothing to maintain the customer's life. And technical stocks performed very well recently due to the CONVID-19, people only can stay home and use their technical product to watch Youtube or Netflix.

Neural Networks are made up of lots of neurons connected. After each neural network receives the input of linear combination, it starts with simple linear weighting and adds a nonlinear activation function to each neuron, so that they can perform nonlinear transformation and output. Each connection between two neurons is a weighted number, called weight. Different weight and activation functions will lead to different outputs of the neural network (**Figure 1**).

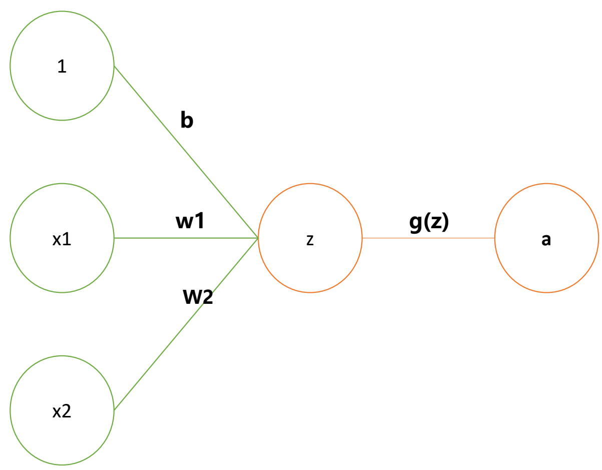

Figure 1. Composition of neural network.

where

$x1$, $x2$ represent the input vector;

w_1, w_2 are the weights, the number of inputs means the number of weights;

b is for bias;

g(z) is the activation function a is the input.

CNN is leveraged to improve supervised and unsupervised models when inputs are pictures. Generally, two-dimension (2D) convolutions are used to learn images, while one-dimension (1D) convolutions can be applied to time series data to extract time features. One-dimension convolution is effective to extract the sequential features from the sequence data. One dimensional convolutional layer can recognize local patterns in a sequence. Since the same input transformation is performed for each sequence segment, the pattern learner at one location in the sentence can later be recognized at other locations, resulting in a one-dimensional convolutional neural network with translational invariance for time translation (**Figure 2**).

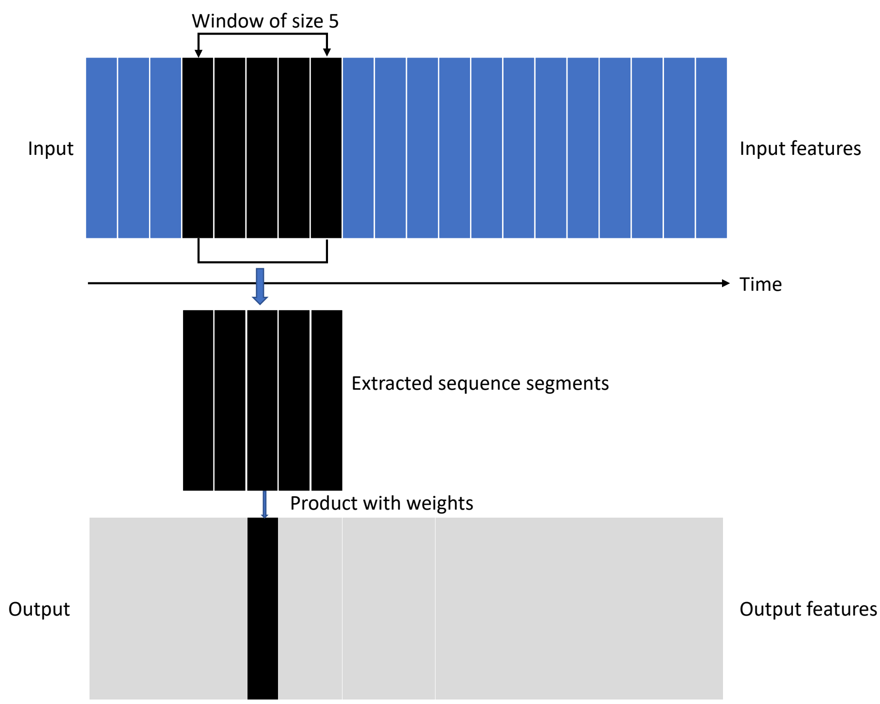

Figure 2. Working principle of 1D CNN: each output time step is obtained by using a small segment of the input sequence in the time dimension.

Long-short term memory is a special type of recurrent neural network (RNN). To explain LNN, Recurrent neural network will be explained first. The training of RNN is similar to the training of traditional neural network. Back propagation algorithm is also applied. As the parameters of the RNN are shared at all times, the gradient of each output depends not only on the calculation of RNN, but also on the calculation of the previous moment. For instance, to calculate the gradient at time $t = 4$, the three previous steps of propagation will be needed and added up their gradients. It is called Backpropagation Through Time (BPTT).

Long-short-term memory was proposed to solve the gradient dispersion problem and the long-range dependency problem of RNN. In traditional RNNs, BPTT is utilized as a training algorithm. However, when the time is relatively long, the residual that needs to be returned will decrease exponentially, leading to the slow update of network weight, which cannot reflect the long-term memory effect of RNN. Therefore, a storage unit is necessary to store memory. Therefore, LSTM was proposed to develop the accuracy of traditional RNNs (**Figure 3**).

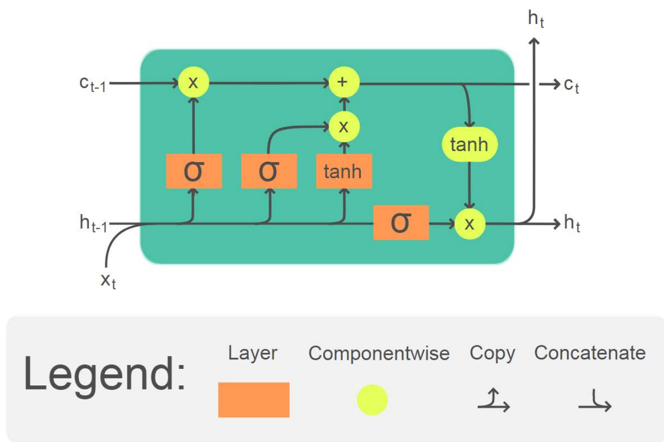

Figure 3. Working principle of LSTM.

where:

σ is the activation function sigmoid;

tan$h$ is activation function tanh;

X is the pointwise multiplication;

+ is pointwise addition.

2.1. Data Collection

The following eight companies in the table are the main companies that introduced many popular technical or Internet products and services to the public (Table 1). To have precise predicted results, 90% of the dataset will be used in training data, while the other 10% data will be test data.

2.2. Experiment

This part will illustrate the process of predicting the adjusted close price of target companies, mainly explaining Apple Company. The reason why the adjusted chosen price is set as a dependent variable is adjusted closing price can reflect the company's real value after accounting for any corporate actions.

Normally, stock values are displayed as the closing price and adjusted closing price. The closing price is the original price, which is the cash value of the last transacted price at the end of a trading day. A stock's price is generally influenced by the supply and demand of the stock market. The company's operation decisions like stock splits, dividends, and rights offerings will influence its stock price. However, traders can receive the precise stock value of the corporate. It is effective when evaluating historical performance as it can provide analysts with an accurate reflection of the practical value of the organization. Besides, the adjusted close price may affect the stock price after the stock market close. Hence, investors can make a trading decision based on the adjusted close prediction.

Before training data, the raw dataset should be processed to the appropriate shape so that it can be trained. Firstly, start with the required packages to run the code, which will be warning, math, NumPy, Matplotlib, Pandas, and Sklearn

Table 1. Target companies.

Symbol	AAPL	AMZN	BABA	NELX	GOOG	FB	PYPL	MSFT
Corporate	Apple Inc.	Amazon.com Inc.	Alibaba Group Holding Limited	Netflix Inc.	Alphabet Inc.	Facebook Inc.	Paypal Holding Inc.	Microsoft

packages. After setting the working directory, the dataset is imported from the CSV file by setting the first column (date) of the dataset as the index.

The below shows the plot of adjusted close price (adj close price) for the entire duration of the observation. If the variables are within [−1, 1], Gradient descent algorithms will improve their performance with faster calculation. MinMaxScaler press the adj close price variables to [0, 1], the MinMax Scaler to the variables is done as follows:

$$x_{scaled} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

The variable scaled_X is utilized in the prediction model. To forecast the original adj close, appropriate transformation is necessary for the prediction model. The dataset is divided into two parts where 90% of the dataset is a train set and 10% of the dataset is a test set. Since the shape of the data is 5198, the train set's shape is set 4680, which is about 90% of the dataset. The test set's shape is 518. The CNN-LSTM is trained on the train set where the operation of the loss function and backpropagation through the gradient descent algorithm is finished the train set. The test set is leveraged to assess the performance of the proposed model. Keras with TensorFlow backend is used to define and train the model.

Then, the independent variables(x) and dependent variables(y) are spilled as train_x, train_y, test_x, and train_y separately. For making the input suitable for the proposed model, the independent variables in the train set and test set are reshaped into 3D arrays. The next step is to define the CNN-LSTM model through Keras. The first layer is Dense, which is the full-connected layer to set the input size. The output shape of the dense layer is (None, 1, 50), where 50 is the setting input size of the next layer. The following layer is 1D convolution by setting the number of filters is 16 and window size is 3.

Then, the Batch Normalization is applied to adjust the distribution of activation values for each layer to have the appropriate breadth. Batch Normalization refers to the unit of every batch in learning and conducts normalization according to batch, which is to normalize the mean value and variance of the data distribution to be 0 and 1. The reason why using Batch Normalization is that it can increase the learning rate and make learning faster and less dependent on initial values. Also, it can inhibit overfitting, which will reduce the necessity for dropout. The following layers are activation function RELU, maxpooling layer, and dense. And the next layers are the LSTM layer and dense layer with the activation function RELU. Then various layers will be included in the model. And mean square error (MSE) is used as the loss function. To train the model, the batch is set as 400, while epochs are 100. The batch is a collection of N samples. Each batch sample is processed independently in parallel. During training, the results of a batch are used to update the model only once. A sample batch is usually closer to the distribution of the total input data than a single input, and the larger the batch is, the more similar it is. However, each batch takes longer to process and still updates the model only once. Epoch often is defined as "one iteration over the entire dataset", which can be used at different stages of training to record and period evaluation.

The Adam algorithm optimizes the weight of the network. It stands for adaptive moment estimation and is widely used to optimize the neural network. Adam applies different learning rates for every weight and updates them with the training movement. Weights' learning rate is updated with an exponentially weighted moving average of the weight's gradients and the squared gradients. The model summary displays a layer of detailed information and structure. Table 2 is the CNN-LSTM model summary.

The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) is used to evaluate the performance of the models. RMSE measures the deviation between the observed value and the true value. And MAE is the average of the absolute error, which can better reflect the actual situation of the predicted value error.

3. Results and Discussion

The proposed CNN-LSTM model predicted the adjusted stock price of eight technical companies. The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) of the eight groups' prediction is shown below. The table and bar chart showing the prediction of Apple has the best performance where RMSE is 3.831866 and MAE is 2.511582. The lowest accuracy is the forecast of Netflix where RMSE and MAE are 144.79596 and 139.614507, which is about 40 times worse than the prediction of Apple (Table 3).

Table 2. CNN-LSTM model summary.

Model: "sequential"		
Layer (type)	Output shape	Param
Dense (Dense)	(None, 1, 50)	350
Conv1d (Conv1D)	(None, 1, 16)	2416
Batch normalization (BatchNo)	(None, 1, 16)	64
Activation (Activation)	(None, 1, 16)	0
Max_pooling1d (MaxPooling1D)	(None, 1, 16)	0
Dense_1 (Dense)	(None, 1, 16)	272
Lstm (LSTM)	(None, 256)	279,552
Dense_2 (Dense)	(None, 1)	257

Table 3. The predicted result of eight companies.

	AAPL	AMAZON	BABA	NETFLIX	GOOGLE	FACEBOOK	PAYPAL	MSFT
RMSE	3.83	96.94	41.03	13.13	144.80	29.84	52.84	9.77
MAE	2.51	88.21	38.39	9.26	139.61	26.53	48.57	7.37

The best fitting of the actual and predicted time series data is also Apple, followed by Microsoft and Amazon companies. Then, Netflix's performance is better than Google's and Facebook's. The worst fitting is Paypal and Alibaba. These may be related to the period and input shape. Even though the period is set as 10 years from 03/01/2000 to 01/09/2020, not all technology companies were launched before 2000. For instance, the earliest date of Paypal trading data is 7/6/2015, therefore the input shape of Paypal prediction is 1312. It leads to the low fitting performance of its forecast model, as the accuracy of the training model will increase with the amount of available data. **Table 4** shows the start date and end date of the time series and the input shape of the model. It can be seen that the input shape of Paypal and Alibaba are the smallest data in these companies. They also have the worst predicting performance. Similarly, Apple, Microsoft, and Amazon have the bigger dataset, which owns the best performance as well. Hence, the performance of the predicted model is related to the size of the data set.

Root Mean Square Error is a typical method to measure the error of the predicting model. And the smaller RMSE, the more accurate of the forecasting model. First, **Table 5** shows the eight companies' RMSE in CNN-LSTM, single LSTM and double LSTM model. The last column is the average RMSE in the three models, which shows double LSTM has lowest RMSE, followed by Single LSTM and CNN-LSTM. Besides, the **Table 5** also indicates double LSTM is the best predicting models in terms of RMSE.

Mean absolute error is the evaluation of errors between paired observations expressing the same phenomenon. In the evaluation of predicting model, it represents the error between the predicted values and actual values. Similar to RMSE, CNN-LSTM had the highest MAE (45.056359), which means it owned poor predicting performance than single LSTM (11.775905) and double LSTM (0.51805). Line plot 5.6 also displayed the same ranking for predicting performance (**Table 6**).

Here will illustrate the fitting results of three models based on their predicting result plots. First of all, Apple Company will be discussed first, since it has the best forecasting performance in three models. The single LSTM model had the best predicting performance, as its predicted data is consistent with the actual data's trend during the whole period. For the CNN-LSTM results, the estimated data fitted the actual data before around the 370th index. Then it started to deviate from the test data after that, which may be because it overfitted the real data at the late stages of training. The double LSTM forecasted worse than the other two models, as its prediction did not coincide with the test at the beginning,

Table 4. Selected data of Companies.

	AAPL	AMAZON	BABA	NETFLIX	GOOGLE	FACEBOOK	PAYPAL	MSFT
Sequence start date	03/01/2000	03/01/2000	22/09/2014	24/05/2002	20/08/2004	21/05/2012	06/07/2015	03/01/2000
End date	31/08/2020	31/08/2020	31/08/2020	31/08/2020	31/08/2020	31/08/2020	31/08/2020	31/08/2020
Input shapes	5199	5211	1509	4600	4048	2096	1312	5211

Table 5. RME performance of three models.

Stock name	AAPL	AMAZON	BABA	NETFLIX	GOOGLE	FACEBOOK	PAYPAL	MSFT	Average
CNN-LSTM	3.83	96.94	41.03	13.13	144.80	29.84	52.84	9.77	49.02
Single LSTM	2.03	58.34	8.00	12.71	33.86	7.79	5.44	3.61	16.47
Double LSTM	0.04	0.06	0.08	0.05	0.04	0.06	0.14	0.05	0.07

Table 6. MAE performance of three models.

	AAPL	AMAZON	BABA	NETFLIX	GOOGLE	FACEBOOK	PAYPAL	MSFT	Average
CNN-LSTM	2.51	88.21	38.39	9.26	139.61	26.53	48.57	7.37	45.06
Single LSTM	1.32	42.05	6.07	9.29	23.45	5.60	4.00	2.44	11.78
Double LSTM	0.03	0.05	0.06	0.04	0.03	0.05	0.12	0.04	0.05

even though its predicted fluctuation was similar to the real trend. However, the CNN-LSTM model can predict more precise fluctuation and numbers, since its forecast was almost the same as the actual data before overfitting. CNN layer of its model structure leads to the great prediction as CNN is effective to extract observations' features. Besides, the single LSTM only can predict the rough trend and price, which is not as precise as the CNN-LSTM model.

Moreover, based on the previous discussion, forecasting performance is related to the size of the data set. The prediction for Paypal will be discussed, as PayPal's prediction didn't have a satisfying performance. Single LSTM is the best prediction model in these three models. As Paypal only had 1312 inputs, which was the 1/4 of Apple's inputs, it is normal that it had poor prediction performance. Even if it has low accuracy, the blow plots can still explain something. For instance, the forecast of the CNN-LSTM deviated from the actual data at the beginning, but it still reflected the fluctuation feature to some extent. And Single LSTM predicted Paypal best, as the trend of predicted data is similar to the real values. Then double LSTM had the lowest accuracy, as it didn't perform the prediction of trend or extract features of values.

Overall, double LSTM had the lowest RMSE and MAE in comparison with CNN-LSTM and single LSTM. However, it had poor performance compared with other predicting models, which may be due to the lack of available datasets. In its forecasted results, observations whose testing data set was bigger than 400 still had great performances. Furthermore, the CNN-LSTM model had the biggest average RMSE and MAE values, which are 49.02 and 45.06 separately. Its predicted result is poorer than single LSTM models. But it showed superiority on extracting features of the dataset, as the result of its training data almost coincided with the actual data before it started overfitting. Last but not least, single LSTM showed great predicting results on accuracy and trend forecast, since all eight forecasts didn't have overfitting or underfitting problems and deviation from test data. However, it can't have more precise predicting results and values, and single LSTM is good at predicting trend of stock price.

4. Conclusions

Technical industry is one of the popular investing areas where investors are interested due to the fourth revolution science and technology. This work tried to improve the predicting accuracy of the stock closing price in technical industry though comparing three deep learning models, which are the CNN-LSTM, single LSTM model and double LSTM model. Convolution Neural Network (CNN) is mainly leveraged to develop supervised and unsupervised models as it can extract the features of input data. One-dimensional (1D) convolution can be applied to catch the time dependencies on the time series data. And Long-short term memory (LSTM) is one of the classic Recurrent Neural Network (RNN), which is widely applied to solve time-series problem. The CNN-LSTM network is made up with conv1d layer, LSTM layer and many functional layers like dense, activation and maxpooling layer, where the single LSTM includes the LSTM layer, dense layer and dropout layer. The double LSTM networks consist of LSTM layer, two dropout layers and two dense layers.

The open, high, low, close and volume variables were used to predict the adjusted close price which can reflect the company's real value. 90% of the dataset was used as training data, while 10% as test data. Though the process of the three predicting models, the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were utilized to evaluate the performance. In eight observed companies, Apple had best prediction results in three predicting models with the lowest RMSE and MAE and the greatest fitting results. It may indicate Apple is worth investing with lower risk and stable return, as the reason why it has great prediction is its company operation and stock return is more stable than other companies.

For the three predicting models, the double LSTM model had the lowest average RMSE and MAE, which means it has the potential to become the more effective prediction model with high accuracy, even though it had the worst prediction results compared with other models in this experiment. The deviation also appears in the double LSTM model. To improve the performance of the double LSTM model, the dropout layer can be set in as larger proportion to avoid overfitting and deviation from test values. Also, the double LSTM model took the longest time to computation with the same numbers of batches and epochs as the other two models. And compared with single LSTM, double LSTM can capture more features. The single LSTM model had the best fitting results without deviation from the actual data. The reason why a single LSTM didn't have an overfitting problem, is as it is a simple model with only one input layer, one LSTM layer, one dropout layer, and one dense layer. Overfitting problems mostly appear on complex models. The double LSTM model and CNN-LSTM model both had overfitting issues, which can be solved by changing the model structure and decreasing the complexity of the model. One of the drawbacks of a single LSTM is it only can predict the rough trend and stock price instead of the precise result. The CNN-LSTM model had the largest RMSE and MAE indicating it may not the best forecasting model. However, it showed accurate prediction with almost the same values as the actual stock price before its trend deviated from real value since the CNN layer is effective to capture the time features. The performance of the CNN-LSTM model can be improved by restructuring its model and changing the layer and parameters to avoid overfitting problems.

5. Limitation

This work also has limitations. Firstly, more companies can be analyzed to avoid the experiment bias, as the eight companies were chosen based experiment designer's subjective opinions. And more companies mean more dataset, which can reduce the probabilities of experiment error. Then, due to the IPO date of eight companies being different, the analyzing time period is different which increased the difficulties to compare observations and prediction models. Also, the parameters of designed model may not the best parameter. To reduce the experimental error, the parameters in three models are set as the same values. For instance, the size of epochs and batches were both set as 100 and 400, and the optimizer method was set as Adam in these three models. However, there are many alternative parameters that can be chosen, which can make predictions more accurate. Moreover, only RMSE and MAE were selected to evaluate the performance of predicting model where the evaluation indexes have Mean Squared Error (MSE) and R Squared as well. Last, there are various structures of the hybrid models, this experiment only used two of them, which cannot represent the whole predicting models. Even the performance of the CNN-LSTM models here is not perfect, which does not mean it's not appropriate to predict the stock price.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

[1] Fama, E.F. (1970) Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, **25**, 383-417. https://doi.org/10.2307/2325486

[2] Bouktif, S., Fiaz, A., Ouni, A. and Serhani, M.A. (2018) Optimal Deep Learning LSTM Model for Electric Load Forecasting Using Feature Selection and Genetic Algorithm: Comparison with Machine Learning Approaches. *Energies*, **11**, Article ID: 1636. https://doi.org/10.3390/en11071636

[3] Edwards, R.D. and Magee, J. (1948) Technical Analysis of Stock Trends. CRC Press, Boca Raton.

[4] Pal, A. and Prakash, P.K.S. (2017) Practical Time Series Analysis: Master Time Series Data Processing, Visualization, and Modeling Using Python. Packt Publishing Ltd.

[5] Ariyo, A.A., Adewumi, A.O. and Ayo, C.K. (2014) Stock Price Prediction Using the ARIMA Model. In 2014 *UKSim-AMSS 16th International Conference on Computer Modelling and Simulation*, Cambridge, 26-28 March 2014, 106-112. https://doi.org/10.1109/UKSim.2014.67

[6] Ma, Y., Han, R. and Wang, W. (2021) Portfolio Optimization with Return Prediction Using Deep Learning and Machine Learning. *Expert Systems with Applications*, **165**, Article ID: 113973. https://doi.org/10.1016/j.eswa.2020.113973

[7] Chowdhury, R., Mahdy, M.R.C., Alam, T.N., Al Quaderi, G.D. and Rahman, M.A. (2020) Predicting the Stock Price of Frontier Markets Using Machine Learning and Modified Black–Scholes Option Pricing Model. *Physica A*: *Statistical Mechanics and its Applications*, **555**, Article ID: 124444. https://doi.org/10.1016/j.physa.2020.124444

[8] Chen, Y. and Hao, Y. (2017) A Feature Weighted Support Vector Machine and K-Nearest Neighbor Algorithm for Stock Market Indices Prediction. *Expert Systems with Applications*, **80**, 340-355. https://doi.org/10.1016/j.eswa.2017.02.044

[9] Allen, D.E., Powell, R.J. and Singh, A.K. (2012) Machine Learning and Short Positions in Stock Trading Strategies. In *Handbook of Short Selling*. Academic Press, 467-478. https://doi.org/10.1016/B978-0-12-387724-6.00032-5

[10] Samitas, A., Kampouris, E. and Kenourgios, D. (2020) Machine Learning as an Early Warning System to Predict Financial Crisis. *International Review of Financial Analysis*, **71**, Article ID: 101507. https://doi.org/10.1016/j.irfa.2020.101507

[11] Vijh, M., Chandola, D., Tikkiwal, V.A. and Kumar, A. (2020) Stock Closing Price Prediction Using Machine Learning Techniques. *Procedia Computer Science*, **167**, 599-606. https://doi.org/10.1016/j.procs.2020.03.326

[12] Göçken, M., Özçalıcı, M., Boru, A. and Dosdoğru, A.T. (2016) Integrating Metaheuristics and Artificial Neural Networks for Improved Stock Price Prediction. *Expert Systems with Applications*, **44**, 320-331. https://doi.org/10.1016/j.eswa.2015.09.029

[13] Pal, A. and Prakash, P.K.S. (2017) Practical Time Series Analysis: Master Time Series Data Processing, Visualization, and Modeling Using Python. Packt Publishing Ltd, Birmingham

[14] Zeroual, A., Harrou, F., Dairi, A. and Sun, Y. (2020) Deep Learning Methods for Forecasting COVID-19 Time-Series Data: A Comparative Study. *Chaos*, *Solitons & Fractals*, **140**, Article ID: 110121. https://doi.org/10.1016/j.chaos.2020.110121

[15] Zhu, X., Wang, H., Xu, L. and Li, H. (2008) Predicting Stock Index Increments by Neural Networks: The Role of Trading Volume under Different Horizons. *Expert Systems with Applications*, **34**, 3043-3054. https://doi.org/10.1016/j.eswa.2007.06.023

[16] Cerchiello, P., Nicola, G., Ronnqvist, S. and Sarlin, P. (2017) Deep Learning Bank Distress from News and Numerical Financial Data. arXiv: 1706.09627. https://doi.org/10.2139/ssrn.3292485

[17] Huang, J., Chai, J. and Cho, S. (2020) Deep Learning in Finance and Banking: A Literature Review and Classification. *Frontiers of Business Research in China*, **14**, Article No. 13. https://doi.org/10.1186/s11782-020-00082-6