Forecasting Market Share Trends using Deep Learning Algorithm

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Abstract: The movement of stock prices is nonlinear and complicated. Non linearity, high noise, complexity, and timing are all characteristics of stock market data. Several experiments have been performed to forecast stock prices, and the conventional stock prediction approach is to construct a linear prediction model based on historical stock data. Some other traditional approaches such as Linear Regression and Support Vector Regression were used but those algorithms did not possess adequate level of accuracy. Due to very high variations in stock prices, various system applied deep learning algorithms due to its proven accuracy in various analytics fields. Artificial Neural Network was deployed to predict stock prices in the existing papers but as stock prices are time-series based, it does not attain certain accuracy. With the intent of making betterment to the existing system, Recurrent Neural Network (RNN) was applied to improve prediction accuracy. In RNN, there is limitation of not able to store high dependencies and vanishing gradient descent issue exists. Therefore, we have constructed and applied the deep learning sequential model, namely Long Short-Term Memory Model(LSTM), into the prediction of stock prices on the next 30 days by using 4 years of historical data. Our input data are carefully selected and applied into the models. The results show that the stock price prediction using LSTM is very efficient and effective over other models .Furthermore, we discovered that the stacked-LSTM model improves the predictive power over LSTM.

Keywords: Long Short Term Memory(LSTM),Recurrent Neural Network(RNN), Root Mean Square Error(RMSE), prediction, stockprices

1.INTRODUCTION

The stock market is the place where the stocks are transferred, traded, and circulated. On the one hand, the issuance of stock provides a legal and reasonable channel for capital flow, which enables a large amount of idle capital to be gathered in the stock market[1].Such effective accumulation of capital can improve the organic composition of enterprise capital and greatly promote the development of economy. On the other hand, the circulation of stock enables the capital to be collected effectively and the accumulation of capitals effectively promoted[2]. Based on this, scholars from all walks of life regard the stock market as an intuitive indicator of a country' sorregion's economic growth over time. One of the main reasons lies in the stock market trading prices can objectively reflect the stock market supply and demand relations[3]. Moreover, the stock market is often regarded as an indicator of stock prices and quantities. However, With the rapid development of social economy, the number of listed companies is increasing, so the stock has become one of the major topics in the financial field. The changing trend of stock often affects the direction of many economic behaviours to a certain extent [4], so the prediction of stock price has been paid more and more attention by scholars. The stockmarket data has the characteristics of non-linear, highnoise, complexity, and timing, etc., [5].Building a linear prediction model based on historical stock data is the traditional stock prediction approach, (Bowden *etal).* [7] proposed to use ARIMA method to build autoregressive model to predict stock prices. Although this approach has some computational advantages, it is limited in its ability to model due to the assumption of statistical distribution and stability of the research data.The outliers in the research data, as well as nonlinear and non-stationary financial time series, have a significant effect on the prediction performance. There are many factors affecting stock prices. In our system, the Long Short Term Memory Model of Deep learning is used to predict stock prices.

PROPOSED WORK

Our system proposes the long short-term memory model to predict stock price trend. In our system, the input of 4 past observed years is given to predict the stock price ofnext30 days. So, if we haveaninputof4 past years, the network output will be thepredictionforthe30nextdays.We'lldivide the data into two groups: Train and Test. The test will be composed of k periods, in which every period is a series of 30days prediction. Using the most accurate forecasting technology, the Long Short-Term Memory unit, which assists investors, analysts, and anyone interested in investing in the stock market by providing them with a clear understanding of the stock market's future situation.

METHEDOLOGY

A. IMPLEMENTATION:

The first step is to import the libraries needed to pre-process the stock data as well as the other libraries needed to create and visualise the LSTM model's outputs. We'll do this with the Keras library, which is part of the Tensor Flow system. Individually, the appropriate modules are imported from the Keras library.

The following step is to visualise the data.We'll upload the local system's stock data as a Comma Separated Value (.csv) file and store it in a Pandas Data Frame using the Pandas Data reader library. Finally, we'll take a look at the details.

B. PRINT THE DATA FRAME SHAPEANDCHECKFORNULLVALUES.

We start by printing the shape of the dataset in this crucial step. We search for null values in the data frame to make sure there aren't any.The presence of null values in a dataset can cause problems during training because they serve as outliers, causing a wide range of results.

C. PLOTTINGTHETRUEADJUSTEDCLOSEVALUE

The Adjusted Close Value is the final performance value that the Deep Learning model would estimate. This value reflects the stock's closing price on any given day of stock market trading.

D. SCALING

We'll scale down the stock values between0 and 1 to reduce the data's computation a lcost. As a result, all of the data in large numbers is reduced, and memory use is reduced. Also, since the data is not spread out in huge values, we can get more accuracy by scaling down. This is achieved by the sci-kit-learn library's Min Max Scaler class.

E. SPLITTINGTOATRAININGSETANDTESTSET

We must divide the entire data set into training and test sets before feeding it into the training model. The Machine Learning LSTM model will be trained on the data in the training set and checked for accuracy and back propagation on the data in the test set.

F. PROCESSING THEDATA FORLSTM

We can feed the data into the LSTM model once it is developed once the training and test sets are ready. Before we can do that, we need to convert the data from the training and test sets into a data type that the LSTM model can understand.

G. BUILDING THE LSTM MODEL Finally, we arrive at the stage of creating the LSTM Model. With one LSTM sheet, we construct a Sequential Keras model. The LSTM layer has32units and is accompanied by a 1 neuron Thick Layer. We compile the model using Adam Optimizer and the Mean Squared Error as the loss function. For an LSTM model, this is the most common combination.

H. TRAININGTHEMODEL

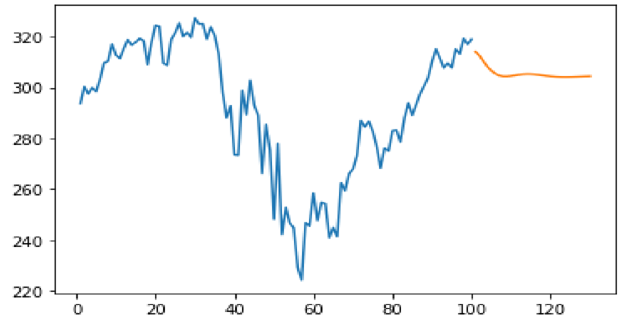
Finally, we use the fit function to train the LSTM model modeled above on the training data for 100 epochs with a batch size of 64.

LSTM PREDICTION

Now that we have our model ready, we can use it to predict the input stock's Adjacent Close Value using the model we trained using the LSTM network on the test set. This is achieved by using the predict function on the LSTM model that has been developed.

I. TRUE VS PREDICTED ADJ CLOSEVALUE–LSTM

Finally, as we predicted the testset's values, we can plot the graph to compare both Adj Close's true values and the LSTM Deep Learning model's predicted value for AdjClose.



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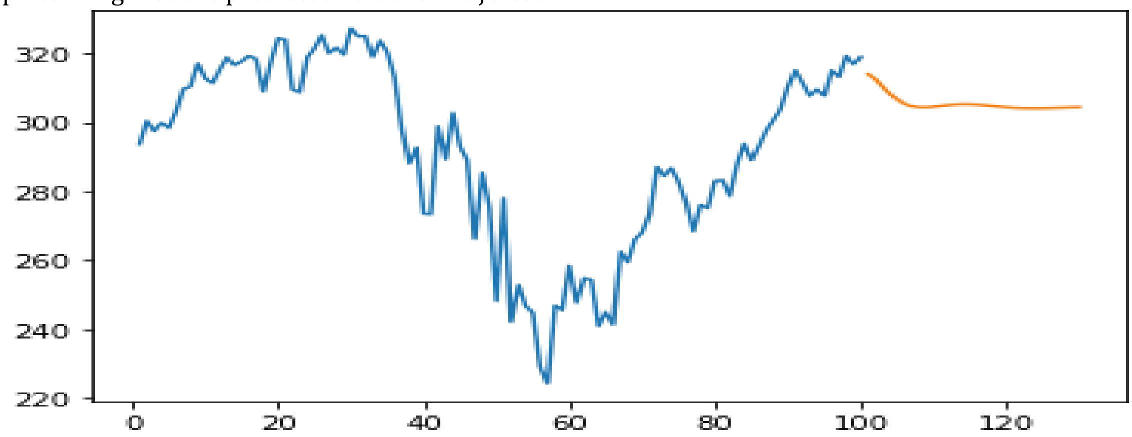

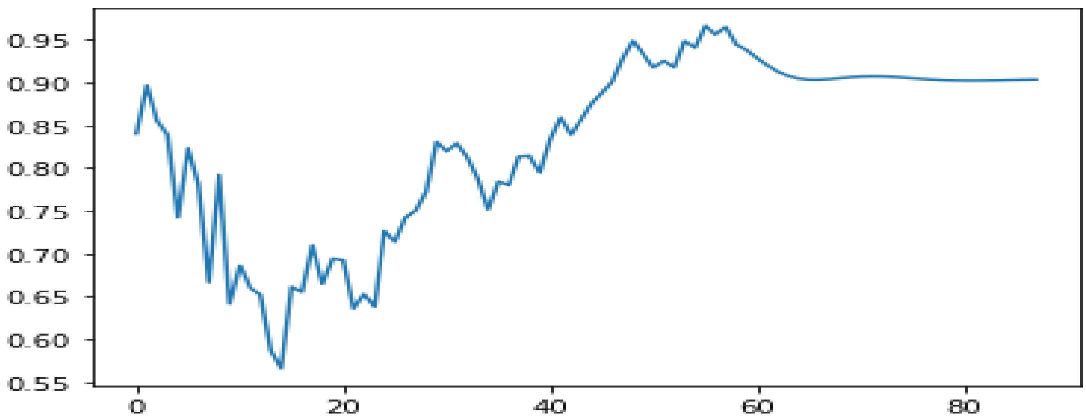

The LSTM network model developed above detects some pattern, as seen in the graph above. We improved the accuracy of the stock value representation by fine-tuning several parameters and adding more LSTM layers to the model.

CONCLUSION

This system establishes a forecasting framework to predict the prices of stocks. We leveraged the combinations of price, volumes, and corporate statistics as input data. We proposed, developed, trained and tested stacked-LSTM models, and built-up trading prediction strategies according to our model. The LSTM shows more superior results over other models due its ability to assign different weights to the input features hence automatically choose the most relevant features. Hence the Stacked-LSTM is more able to capture the long-term dependence in the time series and more suitable in predicting financial time series. Our superior trading return from the LSTM further validates our experimental result. Moreover, we have shown that despite the more complicated model structure of stacked, the stacked-LSTM have better model performance over the single LSTM model due to the potential of over fitting .

FUTURESCOPE

Various algorithms will be used in order to obtain forecasts over a longer period of time and to promote the attainment of higher price prediction accuracy. Dealing with the volatility of stock time series will be one area of potential research. The non-stationary behaviour of the stock market makes it difficult to forecast. It'll be fascinating to see how Stacked-LSTM works on data that has been denoised.

REFERENCE

[1] Devpriya Soni; SparshAgarwal;Tushar Agarwel; Pooshan Arora; Kopal Gupta, "Optimised Prediction Model for Stock Market Trend Analysis ", Eleventh International Conference on contemporary Computing [IC3], 12 November 2018.

[2] Ge Li; Ming Xiao; Ying Guo,"Application of deep Learning in Stock Market valuation Index Forecasting ", IEEE 10th International conference on software Engineering and service science [ICSESS],19 March 2020.

[3] Wei Li; Jian Liao,"A comparative study on trend forecasting approach for stock price time series ", 11thieee International conference on Anti-counterfeiting, security, and Identification [ASID],08 February 2018.

[4] Siyu Yao; Linkai Luo; Hong Peng, " High-Frequency Stock Trend Forecast Using LSTM Model", 13th International Conference on Computer Science & Education [ICCSE], 8-11 Aug, 2018.