IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

STOCK PREDICTION USING LSTM

[1] M. Senthil Kumar, [2] P. Sai Mounish, [3] S. Roach Amalan, [4] K. Ranjith

[1] Associate Professor, [234] UG Scholar

[1234] Department of Computer Science and Engineering,

SRM Valliammai Engineering College, Kattankulathur, Chengalpattu District, India.

Abstract-Predicting the stock market is one of the most difficult tasks in the field of computation. Physical vs. physiological elements, rational vs. irrational conduct, investor sentiment, market rumours, and other factors all play a role in the prediction. All of these factors combine to make stock values extremely volatile and difficult to anticipate accurately. In this arena, we look into data analysis as a game-changer. When all information about a company and stock market events is promptly available to all stakeholders/market participants, the impacts of those events are already embedded in the stock price, according to efficient market theory.. So, it is said that only the historical spot price carries the impact of all other market events and can be employed to predict its future movement. Hence, considering the past stock price as the final manifestation of all impacting factors we employ Machine Learning (ML) techniques on historical stock price data to infer future trends. ML approaches have the potential to uncover previously unseen patterns and insights, which can then be used to generate imprecise predictions. We propose a framework using the LSTM (Long Short Term Memory) model and companies' net growth calculation algorithm to analyze as well as predictions of future growth of a company.

Keywords-Stock price prediction, deep learning, LSTM

I. Introduction

In all businesses, we are always using Data analysis for data-driven decision making. In the stock market, many factors drive the stock price, and the pattern of the price change is not regular. This is why it is tough to take a robust decision on future prices. We use historical stock data to train our model and forecast the stock's future price. This future price is used to calculate the future growth of a company Furthermore, we discovered a predicted growth curve from many companies. A company's stock price is influenced by both intrinsic and extrinsic factors.The stock price of a listed company in a stock exchange varies every time an order is placed for sell or buy and a transaction completes. An exchange collects all sell bids with the expected price per stock (normally it is more than the price paid while bought by the investor) and all buy bids with or without a price limit and a buy-sell transaction is committed when both bids have a match. A company's stock price is influenced by both intrinsic and extrinsic factors.Macroeconomic conditions too play an important role in the growth or decline of a sector as a whole. Some of the intrinsic factors could be the company's net profit, liabilities, demand stability, competition in the market, technically advanced assembly line, surplus cash for adverse situations, stakes in raw material suppliers and finished product distributors, etc. The factors that affect the company stock price are crude oil price, dollar exchange rate, political stability, government policy decision, etc. come under extrinsic attributes. come under extrinsic attributes. Many researchers have tried using historical stock prices as the basis for time series analysis to forecast future stock prices. In recent days different neural network models, and evolutionary algorithms were being applied for stock prediction with success. Deep neural networks like CNN and RNN are also used with different parameter settings and features. We will use a particular sort of RNN called LSTM to predict future firm growth based on past stock prices in this research.

II. Study on related works

Fischer and Krauss in [8] applied long remembering (LSTM) to financial market prediction. The dataset they used is S&P 500 index constituents from Tomson Reuters. They obtained all month-end constituent lists for the S&P 500 from Dec 1989 to Sep 2015, then consolidated the lists into a binary matrix to eliminate survivor bias. The authors also used RMSprop as an optimizer, which may be a mini-batch version of the prop. The primary strength of this work is that the authors used the newest deep learning technique to perform predictions. They relied on the LSTM technique, a lack of information within the financial domain. Although the LSTM outperformed the quality DNN and logistic regression algorithms, the author failed to mention the effort to coach an LSTM with long-time dependencies.McNally et al. [3] leveraged RNN and LSTM on predicting the worth of Bitcoin, optimized by using the Boruta algorithm for the feature engineering part, and it works similarly to the random forest classifier. Besides feature selection, they also used Bayesian optimization to pick out LSTM parameters. The Bitcoin dataset ranged from the 19th of August 2013 to the 19th of July 2016. Used multiple optimization methods to boost the performance of deep learning methods. The primary problem of their work is overfitting. The problem of anticipating Bitcoin price trends is comparable to that of predicting stock market prices. Hidden features and noises embedded within the price data are threats to this work. The study subject was approached as a time sequence problem by the writers. The better part of this paper is the feature engineering and optimization part; we could replicate the methods they exploited in our data pre-processingTo solve the stock selection job, Huang et al. [4] used a fuzzy-GA model.They used the key stocks of the 200 largest market capitalizations listed as the investment universe on the Taiwan Stock Exchange. In addition, for the years 1995 to 2009, the yearly financial statement data and stock returns were obtained from the Taiwan Economic Journal (TEJ) database at www.tej.com.tw/. They ran the fuzzy membership function with GA-optimized model parameters and extracted features for stock scoring optimization. The authors provided a model for stock selection and scoring that was optimised. The authors concentrated on stock rankings, selection, and performance evaluation rather than the prediction model. Their structure is more practical among investors. However, they did not test the model to existing algorithms in the model validation section, instead relying on the benchmark's data, making it difficult to determine whether GA was correct. Hassan and Nath in [9] applied the Hidden Markov Model (HMM) to the stock market forecasting of stock prices of four different Airlines. They divide the model's states into four categories: open price, close price, maximum price, and lowest price. The strength of this paper is that it does not require expert knowledge to construct a prediction model. While this research is limited to the airline industry and evaluated on a short dataset, it may not result in a generalizable prediction model. One of the approaches in stock market prediction related works could be exploited by Shen and Shafiq J Big Data (2020) 7:66 Page 4 of 33 do the comparison work. The authors selected a maximum of 2 years as the date range of the training and testing dataset, which provided us a date range reference for our evaluation part. Dr.M. Senthil Kumar [10] has discussed the software effort estimation techniques in the IT sector and how to predict and estimate future outcomes.

III. Methodology

3.1 LSTM ARCHITECTURE:

In a traditional neural network, final outputs are rarely used as an output for the following step, but if we look at a real-world example, we can see that in many cases, our final output is influenced not only by external inputs, but also by earlier output. For example, when humans read a book, understanding each sentence depends not only on the current list of words but also on the understanding of the previous sentence or on the context that is established through the use of previous sentences. Humans do not start thinking all over again every second. You comprehend each word as you read this essay based on your comprehension of previous words. Classic neural networks do not have the concept of 'context' or 'persistence.' The inability to use context-based reasoning becomes a major limitation of traditional neural networks. Recurrent neural networks (RNN) are conceptualized to alleviate this limitation. RNNs are networked with feedback loops to allow the persistence of information.

IV. Proposed system

This study proposes an attention-based long short-term memory model to predict stock price trends. The model consists of four parts: the input layer, hidden layer, attention layer, and output layer. The input layer cleans the input data to meet the input requirements of the model. The hidden layer is connected to the line model network through the LSTM unit. The attention layer weighted the feature vector. The output layer gets the calculated results. The model training is solvedby a gradient descent algorithm. Figure 1 depicts the proposed framework.

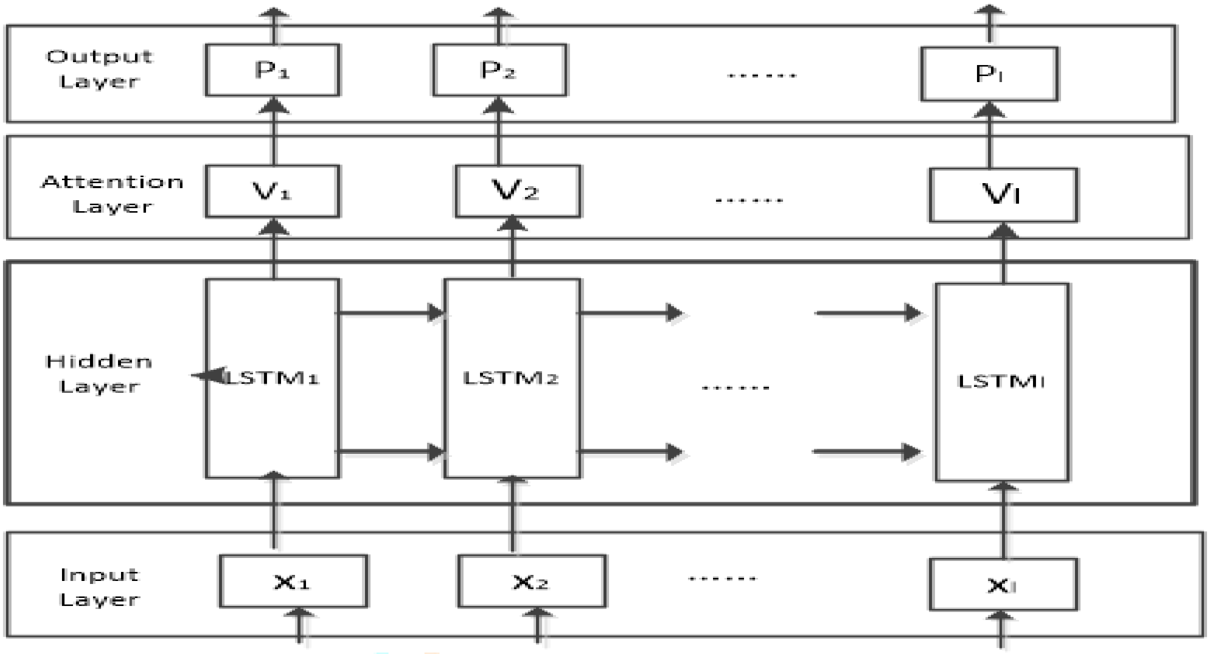

Fig.1 LSTM model

A.Input Layer:

take the date, closing price, opening price, maximum price, and minimum price of the stock as input data to form atime series; (2) split the input data into training set and test set according to the ratio of 7:3; (3) convert each componentof input data into the interval [0,1] after standardization.

B.Hidden Layer:

The hidden layer is formed by the LSTM unit, which is affected by the input data of the current moment and the previous moment.

C.Attention Layer:

By calculating the weights of the input data in the attention layer, the model can select and learn the input data.The higher the weights obtained by the model training, the closer the input data is to the target value.

D.Output Layer:

After the model training is completed, the stock time series isinput for prediction, that is, stock data is input for N days to predict the stock trend on the N+1 day. The trained model uses the trading data of the first four trading days to predict the closing price of the fifth trading day.

V. Implementation

	A	B	C	D	E	F	G
1	Date	Open	High	Low	Close	Adj Close	Volume
2	3/13/1986	0.088542	0.101563	0.088542	0.097222	0.061434	1.03E+09
3	3/14/1986	0.097222	0.102431	0.097222	0.100694	0.063628	3.08E+08
4	3/17/1986	0.100694	0.103299	0.100694	0.102431	0.064725	1.33E+08
5	3/18/1986	0.102431	0.103299	0.098958	0.099826	0.063079	67766400
6	3/19/1986	0.099826	0.100694	0.097222	0.09809	0.061982	47894400
7	3/20/1986	0.09809	0.09809	0.094618	0.095486	0.060337	58435200
8	3/21/1986	0.095486	0.097222	0.091146	0.092882	0.058692	59990400
9	3/24/1986	0.092882	0.092882	0.08941	0.090278	0.057046	65289600
10	3/25/1986	0.090278	0.092014	0.08941	0.092014	0.058143	32083200
11	3/26/1986	0.092014	0.095486	0.091146	0.094618	0.059788	22752000
12	3/27/1986	0.094618	0.096354	0.094618	0.096354	0.060885	16848000
13	3/31/1986	0.096354	0.096354	0.09375	0.095486	0.060337	12873600
14	4/1/1986	0.095486	0.095486	0.094618	0.094618	0.059788	11088000
15	4/2/1986	0.094618	0.097222	0.094618	0.095486	0.060337	27014400
16	4/3/1986	0.096354	0.098958	0.096354	0.096354	0.060885	23040000
17	4/4/1986	0.096354	0.097222	0.096354	0.096354	0.060885	26582400
18	4/7/1986	0.096354	0.097222	0.092882	0.094618	0.059788	16560000
19	4/8/1986	0.094618	0.097222	0.094618	0.095486	0.060337	10252800
20	4/9/1986	0.095486	0.09809	0.095486	0.097222	0.061434	12153600

Fig.2 Collected dataset

Day-wise past stock prices of the selected. Companies are collected from the Bombay stock exchange's official website. Here Microsoft(MSFT) dataset is taken

Thus step incorporates the following:

A) Data discretization: Part of data reduction but with particular importance, especially fornumerical data
B) Data transformation: Normalization
C) Data cleaning: Fill in missing values.
D) Data integration: Integration of data files. After the dataset is transformed into a clean dataset, the dataset is divided into training and testing sets to evaluate. Making a data structure with 60 timesteps and a single output
E) The data properties that will be supplied to the neural network are chosen at this step. In this study Date & Close Price are chosen as selected features.

	Date	Close
0	1986-03-13	0.097222
1	1986-03-14	0.100694
2	1986-03-17	0.102431
3	1986-03-18	0.099826
4	1986-03-19	0.098090
...	...	...
9077	2022-03-17	295.220001
9078	2022-03-18	300.429993
9079	2022-03-21	299.160004
9080	2022-03-22	304.059998
9081	2022-03-23	299.489990

Fig.3 Date and Close time

The training dataset is used to train the NN model. Random weights and biases are used to start the model. The proposed LSTM model consists of a sequential input layerfollowed by 3 LSTM layers with activation. The RNN generated output is compared with the target values and the errordifference is calculated. We repeated the method to forecast the price at various intervals of time. For our case, we took the past 35 years' dataset as training to predict the upcoming years of close price of the share. In this different period, we calculate the percentage of error in the future prediction. For other industries, this would be different. As a result, this will aid in the development of a framework for predicting future company net growth in a specific industry.

VI. RESULT

Fig.4 closing dates of MFST dataset

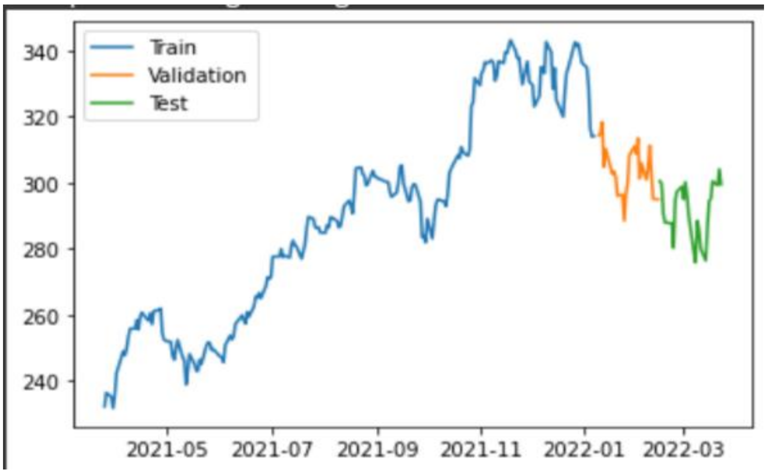

Fig.5 Test and Train of Dataset

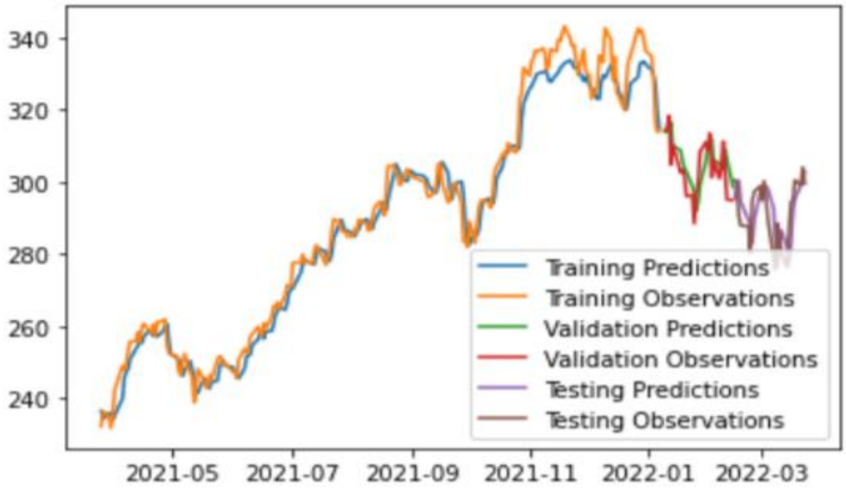

Fig.6 Graph for a given dataset

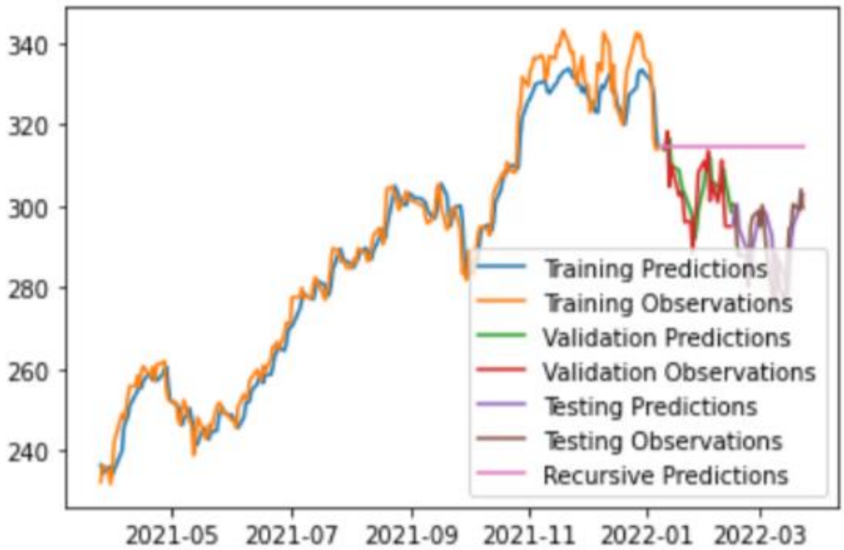

Fig.7 Graph representing future predictions

The output of the model was displayed in Fig.7.The graph contains a straight line that indicates future predictions. The future predictions of the company may be slightly above or below the given line.

VII. CONCLUSION

This study proposes the use of a stacked LSTM network model for predicting stock market behavior, using data from the National Stock Exchange Of India. The model was trained and the results obtained show that the model was able to predict stock market behavior with some accuracy based on the datasets of the company. An open issue remains in that the volatility of the stock market cannot be mitigated using only historic data, but factors of the present also need to be analyzed including current news in the world of politics and economics that could affect the behavior of investors and ipso facto the behavior of stock markets.

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