IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

FORECASTING EQUITY PRICES USING LSTM ALGORITHM

Based on the concepts of Machine Learning

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Abstract: This research paper specifically targets the Indian Stock Market, The National Stock Exchange. Stock Market Prediction refers to understanding various aspects of the stock market that can influence the price of the stocks and based on these potential factors we built a Website/Application to predict the stock's price. We'll be using Python as a programming language to predict the prices, and in this paper, we propose a Machine Learning (ML) approach that will be trained from the available top 50 stocks of the NSE and gain intelligence and then use the acquired knowledge for an accurate prediction. This application with help the user to speculate the stock price trend and help him decide whether to buy or short the stock price to maximize their profit. You can expect to have a decent level of understanding of all the phenomenon and processes of stock market predictions and the associated technologies. This article will cover up topics such as how we created our predictive model and the most popular research methods used in the stock market, and advanced techniques used to predict stock prices using Machine learning. We will also discuss about the challenges and problems faced while creating such advanced predictive model.

Keywords: Stock Market Price Prediction, Long Short Term Memory, Deep Learning, Machine Learning

1.1. INTRODUCTION

Stock, also known as equity, is a security that represents the ownership of a fraction of a corporation. It entitles the owner of the stock to a proportion of the corporation's assets and profits equal to the amount of stock they own. Units of stock are called "shares." A stock is a general term used to express the ownership certificates of any company.

Stock prices change everyday by market forces. Meaning, these prices change because of supply and demand. The price moves up if more people want to buy a stock (demand) than sell it (supply). If more people wanted to sell a stock than acquire it, the price would fall since there would be more supply than demand.

So, why do stock prices change? The most suitable answer for this is that, nobody really knows for sure. Many individuals feel it is impossible to forecast how stock prices will change, but others, including some professionals, believe that by drawing charts and analysing past price movements, you can figure out when to purchase and sell. The only thing we do know as a certainty is that, stock market is volatile and stock prices can change extremely rapidly.

The Main motive of our project is to create a general application for people who randomly enter into stock market without studying the basic concepts e.g Graph study, fundamental analysis and the overview of the company. Though, our model is completely based on LSTM, the prediction accuracy might vary because our algorithm predicts price action based on numericals, but not the news announcements made on that particular share on the previous day.

1.2. PROBLEM STATEMENT

To Accurately predict the future target value for the next day of a given stock based of the previous 60 day price readings. Use a special machine learning and deep learning algorithm available and compare them in terms of graphical analysis. Because only a small dataset is used for training, the accuracy of existing stock market prediction models is relatively low. As a result, the results will be less accurate. There is still a need to explore new features that are more predictable on a regular basis. Despite the fact that multiple algorithms exist, these concepts have yet to be put into practice for the benefit of people. Efficient algorithms should be made available with a user interface that is simple to use.

2.1. METHODOLOGY

This project is made by using Long Short-Term Memory (LSTM) network which is a type of Recurrent Neural Network capable of learning order dependence in sequence prediction problems.

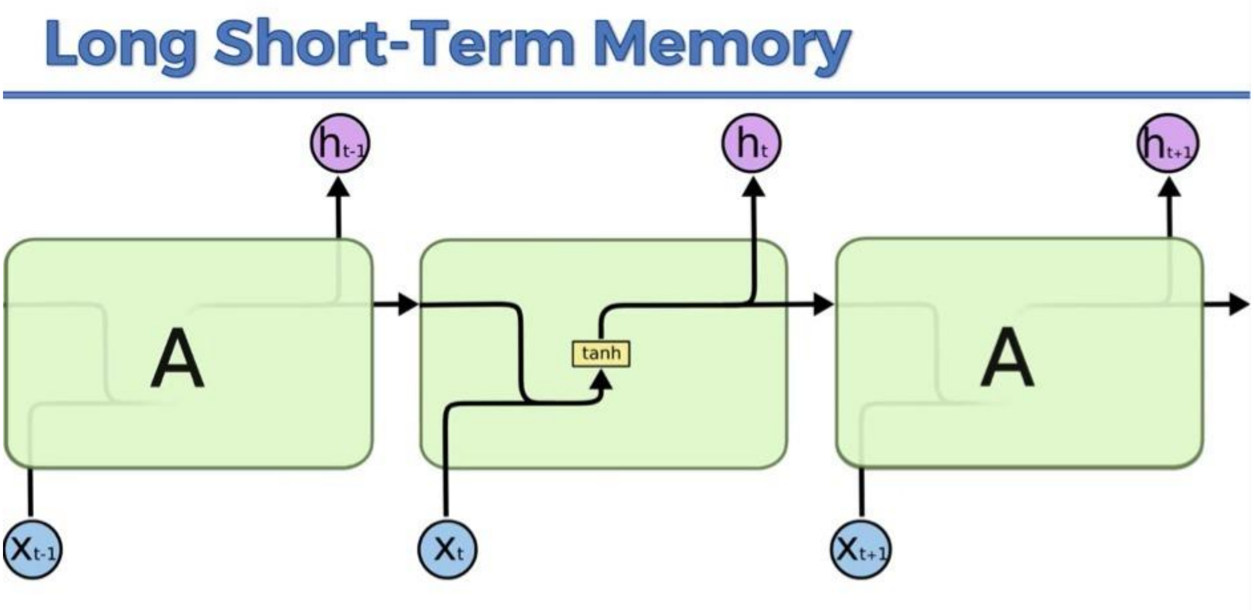


Fig. 1

2.2. RECURRENT NEURAL NETWORK

Recurrent neural networks, also known as RNNs, are a type of neural network that is used to perform sequence analysis. These networks are designed to extract all the contextual information by defining dependencies between numerous time stamps. It consists of numerous successive recurrent layers, and all these layers are sequentially modeled in order to trace the sequence with other sequences. The ability of a recurrent neural network to capture contextual data from a sequence is quite powerful. The contextual cues in the network structure, on the other hand, are stable and effective in achieving the data classification process. Any length of sequence can be processed by RNN.

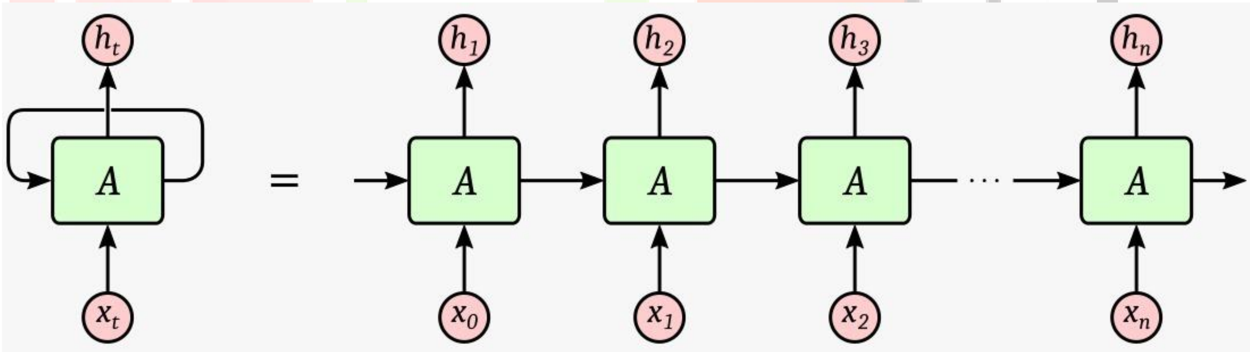


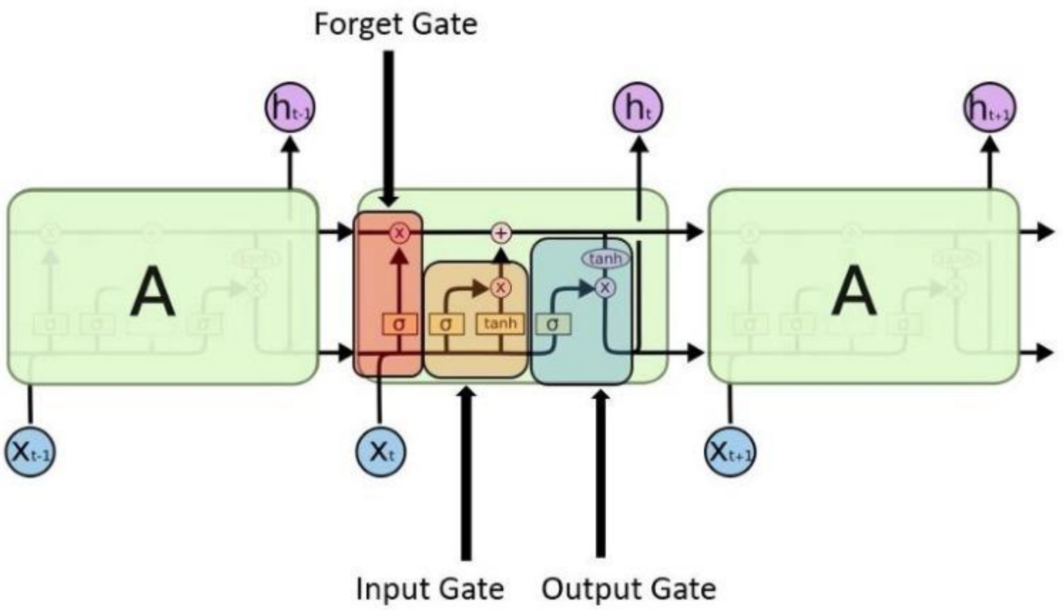
Fig. 2

2.2.1. Advantages of Recurrent Neural Network

1. RNN can model data sequences so that each sample is assumed to be dependent on the ones before it.
2. Even convolutional layers are used with recurrent neural networks to extend the effective pixel neighborhood

2.3. LONG SHORT TERM MEMORY

The long-term dependency problem is explicitly avoided with LSTMs. They don't have to work hard to remember things for long periods of time; it's almost second nature to them.
The memory cell state, which stores the information, is the key to LSTM. It runs the length of the chain in a straight line.
The LSTM can remove or add information to these cell states, which are controlled by gates.
The gates are made of a sigmoid neural network layer and a multiplication operation. The sigmoid layer produces either a zero or a one.



LSTM gates

Fig. 3

2.4. There are three gates to protect and control the cell states:

2.4.1. **Forget Gate** - It determines which details from the block should be removed. The sigmoid function determines this. For each number in the cell state Ct1, it looks at the previous state (ht-1) and the content input (Xt) and outputs a number between 0 (omit this) and 1 (keep this).

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$

Forget gate

Fig. 4

2.4.2. **Input Gate** - It determines which of the input values should be used to modify the memory. The sigmoid function determines which values are allowed to pass through 0,1. and the tanh function assigns weight to the values passed, determining their importance on a scale of -1 to 1.

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

Input gate

Fig. 5

2.4.3. Output Gate - The output is determined by the block's input and memory. The sigmoid function determines which values are allowed to pass through 0,1. and the tanh function multiplies the output of Sigmoid by the weightage given to the values passed, determining their level of importance ranging from -1 to 1.

$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Output gate

Fig. 6

2.4.5. ***Advantages of LSTM.***

1. Because of the constant error backpropagation within memory cells, LSTM is able to bridge gaps.
2. LSTM can handle noise in long time lag problems. Continuous values and distributed representations in contrast to finite state automata or finite state machines, the use of hidden Markov models (LSTM) does not necessitate the selection of a finite number of states a priori. It can deal with an unlimited number of states in theory.
3. LSTM generalizes well — even when the positions of widely differing people are taken into account. It makes no difference if the relevant inputs are separated in the input sequence.
4. No fine-tuning of parameters appears to be required. The LSTM algorithm performs well across a wide range of parameters, including learning rate, input gate bias, and output gate bias. For example, the learning rates used in our experiments may appear high to some readers. A high learning rate, on the other hand, pushes the output gates towards zero, automatically counteracting its own negative effects.
5. The update complexity of the LSTM algorithm per weight and time step is essentially the same as that of BPTT. In comparison to other approaches such as RTRL, this is excellent. Unlike full BPTT, however, LSTM is both spatially and temporally local.

3. LITERATURE REVIEW:

Lei Shei et al. [1] used news data and twitter tweets to develop their neural network model. To match each item, a list of keywords for each company is kept. By emulating, the firm's hashtags in the body of the tweets, the stock-related hashtags was used to extract tweets. The goal is to predict a stock price that is close to the firm's current price. DyNet v1.0 is a neural network library devoted to the study of natural language. DeepClue is built using these programmes. They took Stocks in the S&P 500 index in the US stock market from 2006 to 2015. They take hold of datasets from Yahoo Finance and Reuters and Bloomberg provide financial news.
Yangtuo Peng et al. [2] implemented a model that uses the closing prices of the previous five days to predict future prices. The model looks for all financial publications for sentences including at least one reference to at least one financial institution. They have created a feature vector for DNN input. Each example contains a collection of phrases that were published on the same day. Every sample depends on whether it's favourable ("price-up") or negative ("price-down") on the next day's closing price. The DNN is used in this case, which contains hidden layers (each with 1024 hidden nodes). As a starting point, the historical pricing feature is employed, as well as supplementary data.On top of that, financial news-derived features are added. The predicted stock movement for all unseen stocks is compared to the actual stock movement the next day. Reuters and Bloomberg provided the financial news data for this study. The CRSP database provides historical stock security information (Center for Research in Security Prices).

Xianghui Yuan et al. [3] established a methodology for predicting the stock's excess returns for the month ahead. Over an eight-year period, the financial report, daily opening prices, closing prices, volumes, and other data of the A-share market were used to obtain 60 attributes to be used as input to the model.

Yash Sharma et al. [4] developed Glove which shows how it can be used in sentiment analysis. The RNN receives the word vectors created via the Glove approach, and sentiment analysis performs binary classification (Positive and Negative Sentiments).

Zhu, Maohua, et al[9]. After deciding to use an LSTM neural network for stock prediction, we researched the concept of gradient descent in a number of papers and the various kinds of it We completed our review of the literature by investigating how gradient descent can be used to fine-tune the an LSTM network's weights[9]

Suresh, Harini [10] and[11] Pascanu, Razvan, Tomas Mikolov, and Yoshua Bengio. Examine the major disadvantages of the same and see if we can improve on them. The key issue that we wanted to solve was the correlation between stock data (in the form of dynamic, long-term temporal dependencies between stock prices). A quick search for generic solutions to the aforementioned problem led us to RNNs [10] and LSTM [11].

Jingyi Shen et al. [5] implemented a model to find the price trend by comparing the current closing price to the closing price of n trading days ago. They Use LSTM for time-series prediction to ensure accuracy. This model can capture both complex and hidden data. This collection of data consists of 3558 stocks from the Chinese stock exchange as well. Data gathered via the open-source API and used a web scraping technique for obtaining data from Sina Finance, SWS Research website, web pages.

4. CONCLUSION

In this project, we proposed using data from the Yahoo Finance Market in conjunction with machine learning algorithms to forecast stock index movements. The LSTM algorithm works with a large dataset of data that can be gathered from various global financial markets. LSTM also eliminates the issue of overfitting. For predicting the daily trend of Market stocks, various machine learning-based models have been proposed. The high efficiency is supported by numerical results. Our well-trained predictor was used to create practical trading models. In comparison to the chosen benchmarks, the model generates a higher profit. Because only a small dataset is used for training, the accuracy of existing stock market prediction models is relatively low. As a result, the results will be less accurate.

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[3] Integrated Long-Term Stock Selection Models Based on Feature Selection and Machine Learning Algorithms for China Stock Market-Xianghui Yuan Jin Yuan , Tianzhao Jiang , and Qurat Ul Ain - IEEE Access Fig 4 Sentimental Vector The news data vectorized using TfidfVectorizer Fig 5 StockClue Webapp The Django interface showing all the stock predictions. Table 1 Comparison Table Comparison of our model with other models stated in other approaches from various journals.

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