AReport

on

STOCK PREDICTIONS USING LSTM

Submitted in partial fulfillment of the
requirement for the award of the degree of

Bachelor of Computer Science and Engineering

GALGOTIAS UNIVERSITY
(Established under Galgotias University Uttar Pradesh Act No. 14 of 2011)

Under The Supervision of
Mr. Avjeet Singh

Submitted By

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SCHOOL OF COMPUTING SCIENCE AND ENGINEERING
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GALGOTIAS UNIVERSITY

SCHOOL OF COMPUTING SCIENCE & ENGINEERING

PROGRESS REPORT ETE VIVA

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B.Tech., / BCA / B.Sc., / M-Tech., / MCA / M.Sc.,

Project Details: **Semester:** 3 **Project ID:** BT2004

Project Title	Prediction of Stocks using LSTM Neural Network
Progress of Project (in words)	we started with studying some case studies on google regarding LSTM & Neural Network. we studied about stock value also. Then after that we wrote ~~this~~ research paper.
Research Paper Title	Predicting Stock Prices Using LSTM
Progress of Research Paper	Research paper written, everything is finalized,

ETE VIVA DETAILS:

ETE VIVA DATE	ETE VIVA TIME	ROOM NO

Student Progress Details (Filled by Guide Only):

S. No	Name	Admission Number	No. Of time Came for Discussion	Performance of Student	Approval for Review 1
1	Kirandeep Kaur	20SCSE1180048	2	☐ Satisfactory ☑ Good ☐ Poor	☑ Approved ☐ Not Approved
2	Naman Sharma	20SCSE1180020	2	☐ Satisfactory ☑ Good ☐ Poor	☑ Approved ☐ Not Approved
3				☐ Satisfactory ☐ Good ☐ Poor	☐ Approved ☐ Not Approved

24/12/21

Guide Name & Signature with Date **Reviewer Name & Signature with Date**

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CANDIDATE'S DECLARATION

I/We hereby certify that the work which is being presented in the thesis/project/dissertation, entitled **"STOCK PREDICTION USING LSTM."**in partial fulfillment of the requirements for the award of the BTech CSE AI and ML submitted in the School of Computing Science and Engineeringof Galgotias University, Greater Noida, is an original work carried out during the period of month, Year to Month and Year, under the supervision of Name… Designation, Department of Computer Science and Engineering/Computer Application and Information and Science, of School of Computing Science and Engineering , Galgotias University, Greater Noida

The matter presented in the thesis/project/dissertation has not been submitted by me/us for the award of any other degree of this or any other places.

Kirandeep Kaur Dhillon, 20SCSE1180048

Naman Sharma – 20SCSE1180020

This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Mr. AvjeetSingh

A Project Review-2 Report

ON

STOCK PRICE PREDICTION USING LSTM NEURAL NETWORK

Submitted in partial fulfillment

of the requirement for the

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ABSTRACT

In the finance world stock trading is one of the most important activities. Stock market prediction is an act of trying to determine the future value of a stock other financial instrument traded on a financial exchange. This paper explains the prediction of a stock using Machine Learning. The technical and fundamental or the time series analysis is used by the most of the stockbrokers while making the stock predictions. The programming language is used to predict the stock market using machine learning is Python. In this paper we propose a Machine Learning (ML) approach that will be trained from the available stocks data and gain intelligence and then uses the acquired knowledge for an accurate prediction. In this context this study uses a machine learning technique called Support Vector Machine (SVM) to predict stock prices for the large and small capitalizations and in the three different markets, employing prices with both daily and up-to-the-minute frequencies..
Various learning models /architectures are already available for stock price prediction of a particular company.

- Multi layer Perceptron's(MP)
- Artificial Neural Networks
- Long Short-Term Memory Model(LSTM)

Based on historical prices available as data, these models are used to forecast stock prices.

Predicting stock market prices is a complex task that traditionally involves extensive human-computer interaction. Due to the correlated nature of stock prices, conventional batch processing methods cannot be utilized efficiently for stock market analysis. We propose an online learning algorithm that utilizes a kind of recurrent neural network (RNN) called Long Short Term Memory (LSTM), where the weights are adjusted for individual data points using stochastic gradient descent. This will provide more accurate results when compared to existing stock price prediction algorithms. The network is trained and evaluated for accuracy with various sizes of data, and the results are tabulated. A comparison with respect to accuracy is then performed against anArtificial Neural Network.

It has never been easy to invest in a set of assets, the abnormally of financial market does not allow simple models to predict future asset values with higher accuracy. Machine learning, which consist of making computers perform tasks that normally requiring human intelligence is currently the dominant trend in scientific research. This article aims to build a model using Recurrent Neural Networks (RNN) and especially Long-Short Term Memory model (LSTM) to predict future stock market values. The main objective of this paper is to see in which precision a Machine learning algorithm can predict and how much the epochs can improve our model.

CHAPTER-1

INTRODUCTION

The stock market is a vast array of investors and traders who buy and sell stock, pushing the price upor down. The prices of stocks are governed by the principles of demand and supply, and the ultimate goal of buying shares is to make money by buying stocks in companies whose perceived value (i.e., share price) is expected to rise. Stock markets are closely linked with the world of economics — the rise and fall of share prices can be traced back to some Key Performance Indicators (KPI's). The five most commonly used KPI's are the opening stock price (`Open'), end-of-day price (`Close'), intraday low price (`Low'), intra-day peak price (`High'), and total volume of stocks traded during the day (`Volume'). Economics and stock prices are mainly reliant upon subjective perceptions about the stock market. It is nearimpossible to predict stock prices to the T, owing to the volatility of factors that play a major role in the movement of prices. However, it is possible to make an educated estimate of prices. Stock prices never vary in isolation: the movement of one tends to have an avalanche effect on several other stocks as well . This aspect of stock price movement can be used as an important tool to predict the prices of many stocks at once. Due to the sheer volume of money involved and number of transactions that take place every minute, there comes a trade-off between the accuracy and the volume of predictions made; as such, most stock prediction systems are implemented in a distributed, parallelized fashion . These are some of the considerations and challenges faced in stock market analysis.

Data analysis have been used in all business for data-driven decision making. In share market, there are many factors that drive the share price, and the pattern of the change of price is not regular. This is why it is tough to take a robust decision on future price. Artificial Neural Network (ANN) has the capability to learn from the past data and make the decision over future.

Almost every country has one or more stock exchanges, where the shares of listed companies can be sold or bought. It is a secondary market place. When a company first lists itself in any stock exchange to become a public company, the promoter group sells substantial amount of shares to public as per government norms. During incorporation of a company shares are bought by promoter groups or institutional investors in a primary market. Once promoter offloads major portion of the shares to public relail investors, then those could be traded in secondary market i.e. in stock exchanges. In India the BSE(Bombay Stock Exchange) and the NSE(National Stock Exchange) are the two most active stock exchange. The BSE has around 5000 listed companies where as NSE had around 1600. Both the exchange has similar trading mechanism and market open time, closing time and settlement process. Stock exchanges helps individual investors to take part in the share market and allows to buy even a single share of some listed company with the help of a trading account and demat account. These online markets have revolutionized the Indian investment arena along with government initiative like tax benefit on equity investment, National Pension Scheme (NPS) investing in share market etc. Due to continuous reduction in bank inrest rates and increasing inflation middle class investors are moving towards equity market from the safe heaven of fixed deposites. All these have helped to grow the capitalization of both the exchanges.

Stock markets tend to be extremely volatile and also create huge amounts of data on each trading day. A place where stocks or shares of listed companies are traded is stock market. It consists of two components,

1. Primary
2. Secondary.

Primary market can be defined as a place where issues are introduced newly through IPOs abbreviated as Initial public offerings, whereas in secondary market, investors will trade on derivatives / securities that are owned by them. Stock markets follow non-linear time series containing high fluctuating data. Because of its random nature, prediction involves risks compared to other sectors. the future stock prices of State Bank of India (SBIN) are predicted using the LSTM Recurrent Neural Network. Our task is to predict stock prices for a few days, which is a time series problem. The LSTM model is very popular in time-series forecasting, and this is the reason why this model is chosen in this task. The historical prices of SBIN are collected automatically using the nsepy library of python. We have used 6 years of historical price data, from 01.01.2013 to 31.12.2018. This data set contains 1483 observations with 12 attributes. After preprocessing, only dates and OHLC (Open, High, Low, Close) columns, a total of 5 columns, are taken as these columns have main significance in the dataset. The LSTM model is trained on this entire dataset, and for the testing purpose, a new dataset is fetched for the duration between 01.01.2019 to 18.09.2019. The stock prices for this new duration will be predicted by the already trained LSTM model, and the predicted prices will be plotted against the original prices to visualise the model's accuracy.

LSTM Architecture

An overview of Recurrent Neural Network (RNN) In a classical neural network, final outputs seldom act as an output for the next step but if we pay attention to a real-world phenomenon, we observe that in many situations our final output depends not only the external inputs but also on earlier output. For example, when humans read a book, understanding of 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 created using past sentences. Humans donIt start their thinking from scratch every second. As you read this essay, you understand each word based on your understanding of previous words. This concept of "contextI or "persistenceI is not available with classical neural networks. Inability to use context-based reasoning becomes a major limitation of traditional neural network. Recurrent neural networks (RNN) are conceptualized to alleviate this limitation.RNN are networked with feedback loops within to allow persistence of information. The Figure 1. , shows a simple RNN with a feedback loop and its unrolled equivalent version side by side. Initially (at time step t) for some input Xt the RNN generates an output of ht. In the next time step (t+1) the RNN takes two input Xt+1 and ht to generate the output ht+1. A loop allows information to be passed from one step of the network to the next. RNNs are not free from limitations though. When the "context‖ is from near past it works great towards the correct output. But when an RNN has to depend on a distant "context‖ (i.e. something learned long past) to produce correct output, it fails miserably. This limitation of the RNNs was discussed in great detail by Hochreiter and Bengio, et al. . They also traced back to the fundamental aspects to understand why RNNs may not work in long-term scenarios. The good news is that the LSTMs are designed to overcome the above problem.

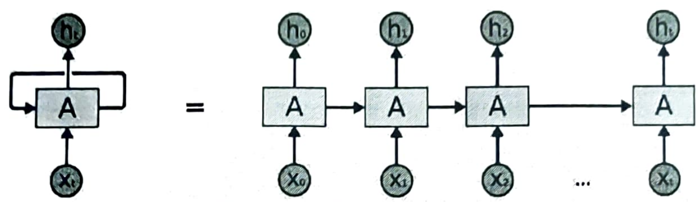

Figure 1: An unrolled recurrent neural network

CHAPTER-2

LITERATURE SURVEY

Long Short-Term Memory (LSTM) is one of many types of Recurrent Neural Network RNN, it's also capable of
catching data from past stages and use it for future predictions [7]. In general, an Artificial Neural Network (ANN)
consists of three layers:
1) input layer,
2) Hidden layers,
3) output layer.
In a NN that only contains one hidden layer the number of nodes in the input layer always depend on the
dimension of the data, the nodes of the input layer connect to the hidden layer via links called 'synapses'. The
relation between every two nodes from (input to the hidden layer), has a coefficient called weight, which is the
decision maker for signals.

Artificial Neural Networks

Artificial neural networks are basically designed to fathom complicated issues that normal machine learning algorithms or easy neural networks cannot. ANNs are connected in a simpler way that they don't do huge weightlifting of human brain which is having around 86 billion neurons, in a complex and complicated web of interconnectivity. Deep learning is considered as part of machine learning. In fact, machine learning helps in creating models that are better at assignments allotted to them. If a machine learning algorithm provides inaccurate and non-obvious results, the developers will take adequate steps to amend. Models of deep learning that uses Artificial Neural Networks simulates the working of a human brain and obviously determines accuracy of the predictions on its own, without the intervention of human brain. Artificial neural networks are capable of learning what they parse and can generalize or create patterns with the derived knowledge. Such powerful faculty is often taken for granted as human brains perform such tasks automatically. ANNs are far different from the existing traditional methods in training or precisely programming systems as they need detailed rules, which cover at the outset each possible outcome. The process of discriminating the category into which piece of data belongs to can be defined as classification task;

Prominent use of this approach is in programming a neural network. Such ability in classifying live patterns or examples is generalization.

There are lots of research work in stock market prediction as well as in LSTM. Almost every data mining and prediction techniques were applied for prediction of stock prices. Many different features and attributes were used for the same purpose. There are three main categories of stock market analysis and prediction such as (a) Fundamental analysis, (b) Technical analysis and (c) Time series analysis. Most of the stock forecasting techniques with time series data normally use either a linear such as AR, MA, ARIMA, ARMA, CARIMA, etc. , or non-linear models (ARCH, GARCH, ANN, RNN, LSTM, etc.).Authors in have analyzed many different macro-economic factors by designing a data warehouse that affects share price movement such as crude oil price, exchange rate, gold price, bank interest rate, political stability, etc. Researchers in employed frequent itemset mining technique to find a lagged correlation between price movement between different sectorial index in Indian share market. Roondiwala et al. in has used RNN-LSTM model on NIFTY-50 stocks with
4 features (high/close/open/low price of each day). They have used 21 days window to predict the next day price movement. A total of 5 years data has been used for prediction and RMSE as error metric to minimize with backpropagation.
Kim et al. in proposed a model, 'the feature fusion long short-term memory-convolutional neural network (LSTM-CNN) model'. They have used CNN to learn the features from stock chart images. They found that the candlestick charts are the best candidate for predicting future stock price movement. Next they employed LSTM and fed with historical price data. They have tested on minute-wise stock price and used 30 minute sliding window to forecast 35th minute price. They have tested on S&P 500 ETF data with stock price and trade volume using CNN. They use the CNN and LSTM individually on different representation of the same data and then used the combined feature fusion model for the same purpose. It is observed that the combined model outperforms individual models with less prediction error. Thus this work establishes the fact that different representation of the same data (raw stock price and trade volume and stock chart image) with combined models where each individual model is optimized for separate data format can learn more intrinsic data dynamics and features which is alalogous to looking on the same object from different perspective angles that gives new insight. Hiransha et al.in their paper , employed three different deep learning network achitectures such as RNN, CNN and LSTM to forecast stock price using day wise past closing prices. They have considered two company from IT sector (TCS and Infosys) and one from Pharma sector(Cipla) for experiment. The uniqueness of the study is that they have trained the models using data from a single company and used those models to predict future prices of five different stocks from NSE and NYSE (Newyork Stock Exchange). They argued that linear models try to fit the data to the model but in deep networks underlying dynamic of the stock prices are unearthed. As per their results CNN outperformed all other models as well as classical linear models. The DNN could forecast NYSE listed companies even though the model

has learned from NSE dataset. The reason could be the similar inner dynamics of both the stock exchanges. Gers & Schmidhuber proposed a variation of LSTM by introducing "peephole connections" . In this model the gate layers can look into the cell state. In another case the model coupled forget and input gates. In this case, decision to add new information or to forget it is taken together. It forgets only when it needs to input something in its place. This architecture inputs new values to the cell state when it forgets anything older. Cho, et al. proposed another popular LSTM variation known as the Gated Recurrent Unit (GRU). It aggregates both the forget and input gates into an "update gate." The cell state and hidden state are merged along with a few other minor modifications to make the final model more simple than the original LSTM. Due to the above reason this model is becoming popular day by day. These are by no means an exhaustive list of modified-LSTMs. There are many other variants such as Depth Gated LSTMs by Yao, et al. . Koutnik, et al. proposed 'Clockwork RNNs' to tackle long-term dependencies in a completely different manner. **LSTM Networks** Hochreiter & Schmidhuber [10] introduced a special type of RNN which is capable of learning long term dependencies. Later on many other researchers improved upon this pioneering work in [11] [12] [13] [14]. LSTMs are perfected over the time to mitigate the long-term dependency issue. The evolution and development of LSTM from RNNs are explained in [15] [16]. Recurrent neural networks are in the form of a chain of repeating modules of the neural network. In standard RNNs, this repeating module has a simple structure like a single tanh layer as shown in Figure 2. LSTMs follow this chain-like structure, however the repeating module has a different structure. Instead ofhaving a single neural network layer, there are four layers, interacting in a very special way as shown in Figure 3. In Figure 3, every line represents an entire feature vector, from the output of one node to the inputs of others. The pink circles represent pointwise operations, like vector addition, while the yellow boxes are learned neural network layers. Lines merging denote concatenation, while a line forking denotes its content being copied and the copies going to different locations. The Working of LSTM The key to LSTMs is the cell state, the horizontal line running through the top of the diagram.The cell state is like a conveyor belt. This runs straight down the entire chain, having some minor linear interactions. LSTM has the ability to add or remove information to the cell state, controlled by structures called gates. Gates are used for optionally let information through. Gates are composed of a sigmoid neural net layer and a pointwise multiplication operation. The sigmoid layer outputs numbers between 0 and 1, describing how much of each component should be let through. A value of 0 means "let nothing through," while a value of 1 means "let everything through!"An LSTM has three of these gates, to protect and control the cell state. The first step of LSTM is to decide what information are to be thrown out from the cell state. It is made by a sigmoid layer called the "forget gate layer." It looks at ht−1ht−1 and xtxt, and outputs a Stock Price Prediction Using LSTM on Indian Share Market A. Ghosh et al. 105 number between 00 and 11 for each number in the cell state Ct−1Ct−1. A 11 represents "completely keep this" while a 00 represents "completely remove this." In the next step it is decided what new information are going to be stored in the cell state. It has two parts. First, a sigmoid layer called the "input gate layer" decides which values are to be updated. Thereafter, a tanh layer creates a vector of new candidate values, C~tC~t, that could be added to the state. In the next step, these two are combined to create an update to the state. It is now time to update the old cell state, Ct−1Ct−1, into the new cell state CtCt. We multiply the old state by ftft.

Then we add it$C~tit$C~t. This is the new candidate values, scaled by how much we decide to update each state value. Finally, we need to decide on the output. The output will be a filtered version of the cell state. First, we run a sigmoid layer which decides what parts of the cell state we're going to output. Then, we put the cell state through tanh-tanh (to push the values to be between −1−1 and 11) and multiply it by the output of the sigmoid gate, so that we only output the parts we decided to.

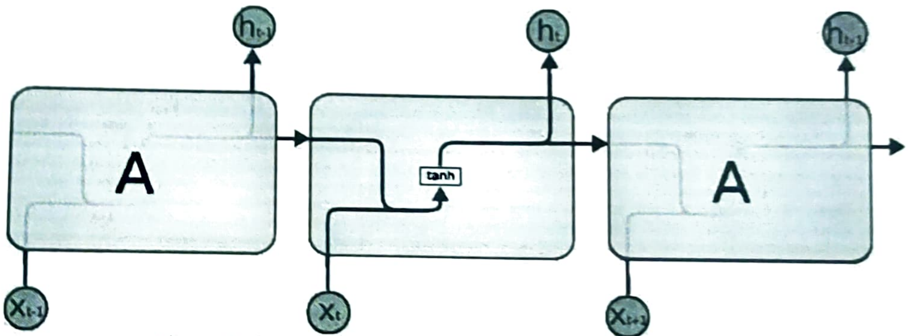

Figure 2: The repeating module in a standard RNN contains a single layer

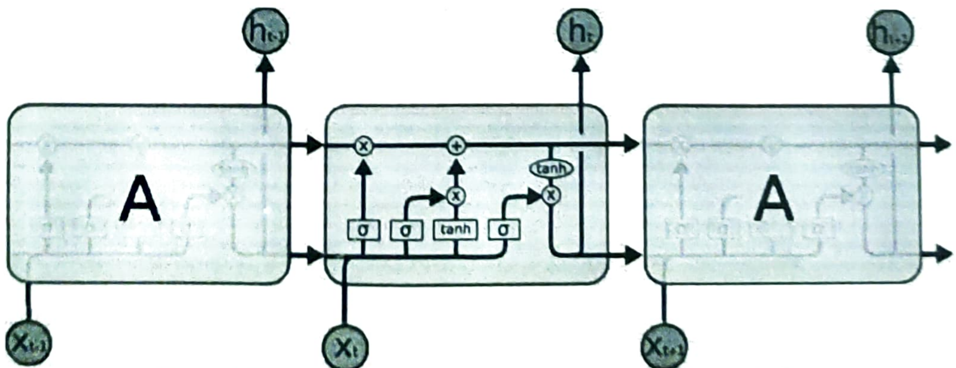

Figure 3: The repeating module in an LSTM contains four interacting layers

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