ISSN 2278-3091
Volume 9, No.5, September - October 2020
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse195952020.pdf
https://doi.org/10.30534/ijatcse/2020/195952020

# A Model for Stock Price Predictions Using Deep Learning Techniques

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## ABSTRACT
Nowadays most of the people are started investing their money in stocks. Stock market prediction is to determine the future value of a company stock on a financial exchange. The successful prediction of a stock's future price will increase investor's profits. Stock market trading results frequently change stock price which is risk for investors to invest or predict the behavior, and difficult for a company to know its financial status.

The value of a stock is given by its open price on the stock and the number of stocks traded. The more a share is traded, the more it is valuable, and conversely, if a share is put into trade in a low volume, it is not valuable for some traders and by default its value decreases. This expectation of the market can generate profits or losses, depending on capacity to predict future values. Therefore, the problem becomes: for a given stock market history prices, determine the movement of open or close price for generating profit.

Various algorithms have been designed by using different learning techniques but have failed to provide an accurate prediction of any stock movement. A few algorithms in Artificial Intelligence, namely Machine Learning, tried to solve the problem described above. Some of them are ARIMA (autoregressive integrated moving average), ANN (Artificial Neural Networks). But all these models could not support long-term dependencies.

LSTM (long short term memory) one of the Recurrent Neural Networks is used in this model to predict stock price and it supports long-term dependencies. In this paper we have trained LSTM over stock market data set. It is making predictions with good accuracy. This model will be useful for investors to invest in market, based on various factors. These predicted and analyzed data can be observed by an individual to know financial status of companies and their comparison. The main feature is to observe share market prices and generate patterns from large datasets, to predict an approximate value of share price.

**Key words:** Artificial Neural Networks, Auto Regressive Integrated Moving Average, Long Short Term Memory, Stock

## 1. INTRODUCTION
Stock price prediction is nothing but predicting future price of the stock trading on the exchange [1]. Here many people are investing billion dollars of money sometimes they are in profits and sometimes they are in loses. Many researchers are trying to provide a scientific solution for early stock price prediction by analyzing the historical stock opening and closing values [2-7].

In that process some of the researchers used predict stock prices but these results are not that much satisfactory may be because stock prices are very dynamic in nature so it is very difficult to achieve accurate predictions in Figure 1 a snap of vijaya bank stock price graph was given that shows dynamic nature of the stock prices over time.

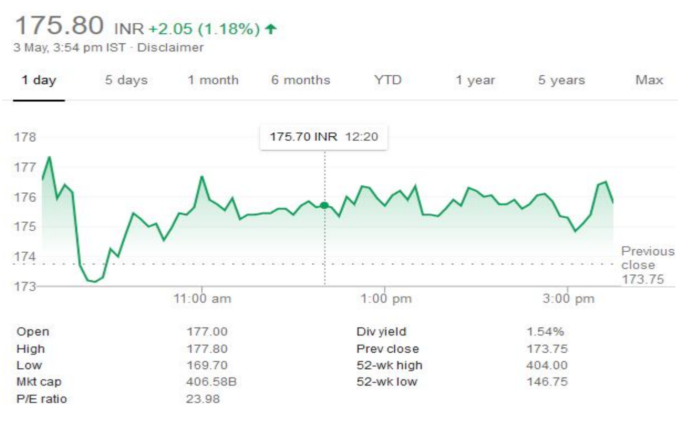


**Figure 1:** Vijaya bank stock price graph

Even not only dynamic nature of the data there are so many other factors influence stock price such as political, psychological, climate, world political scenarios, war conditions etc.

In historical models which are predicting time series data are using moving average in these models average of series of points will be taken so that seasonal are speculations can be avoided [8].Exponential smoothening also another technique used to predict future values it almost like moving average but some changes are added in prediction like new value is nothing but old value plus error. It may be seasonal or irregular speculations data prediction in historical models are shown in Figure 2. Deep learning models are effective for this type of applications [9-10].

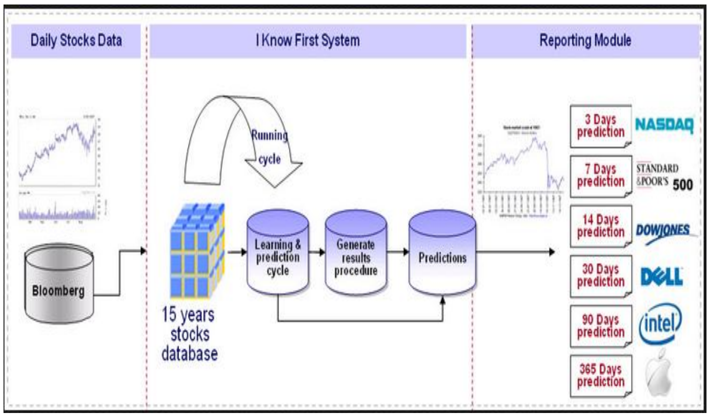


**Figure 2**: Architecture for stock prediction using traditional models

## 2. LITERATURE SURVEY

Now a day, Stock price prediction is difficult problems. Where stock movement prediction is a time series problem. Estimating of this using a Statistical algorithm will resolve many of the current stock price prediction problems. Machine Learning is a field of Computer Science that gives Computers the ability to learn. There are various types of machine learning algorithms. They are Supervised Learning and Unsupervised Learning. The process of training a machine learning model involves providing an algorithm and the data so that model learns its parameters from the provided training data.

Predicting stock market behavior is very attractive area by both academic and industry researchers. The authors Leonardo Dos Santos Pinheiro and Mark Dras have discussed an automated trading of a company based on the information about that company from various sources like news, print media, electronic media, etc, [11].All feed forward methods are not consistent on previous outcome in any traditional neural networks [12].

The authors Yumo Xu and Shay B. Cohen built a trading-day alignment model based on StockNet [13]. Lin et al. proposed stock market forecasting model using Support Vector Machine. It is used in predicting and controlling of decent subset features and overfitting for assessing stock indicator [14].Xiao Ding et al. discussed a deep learning method for event-driven stock market prediction, various types of events influenced on predicting stock price movements [15].

The generative models are used to estimate stock signal and randomness as sentimental analysis than discriminative models [16].Navid Rekabsaz et al. addressed the stock market forecast volatility using sentimental analysis methods. Not only the sentimental analysis but also used Information Retrieval (IR) term weighted text frequency methods [17].

The authors Ziniu Hu et al. have developed a hybrid method for stock prediction using Hybrid Attention Networks based sequence of related online news. The learning of human being facing through online news is processed in sequential content dependency, diverse influence, and effective and efficient learning [18].

A novel approach for mining text from real time news and thus predicting the stock prices was proposed in the paper by Pui Cheong Fung, et al [19]. A framework by combining of auto encoders, long-short term and wavelet transforms suggested by W. Bao et al. [20].

## 3. METHODOLOGY

In this paper we have used LSTM long short term memory model to address limitations in traditional Recurrent Neural networks such as vanishing gradient and exploding gradient. To train the model we have used following stock market data.

**Table1 :** Sample stock price dataset

| Index | Date | Open | High | Low | Close | Volume |
|---|---|---|---|---|---|---|
| 0 | 1/3/2012 | 325.25 | 332.83 | 324.97 | 663.59 | 7,380,500 |
| 1 | 1/4/2012 | 331.27 | 333.87 | 329.08 | 666.45 | 5,749,400 |
| 2 | 1/5/2012 | 329.83 | 330.75 | 326.89 | 657.21 | 6,590,300 |
| 3 | 1/6/2012 | 328.34 | 328.77 | 323.68 | 648.24 | 5,405,900 |
| 4 | 1/9/2012 | 322.04 | 322.29 | 309.46 | 620.76 | 11,688,800 |
| 5 | 1/10/2012 | 313.7 | 315.72 | 307.3 | 621.43 | 8,824,000 |
| 6 | 1/11/2012 | 310.59 | 313.52 | 309.4 | 624.25 | 4,817,800 |
| 7 | 1/12/2012 | 314.43 | 315.26 | 312.08 | 627.92 | 3,764,400 |
| 8 | 1/13/2012 | 311.96 | 312.3 | 309.37 | 623.28 | 4,631,800 |
| 9 | 1/17/2012 | 314.81 | 314.81 | 311.67 | 626.86 | 3,832,800 |
| 10 | 1/18/2012 | 312.14 | 315.82 | 309.9 | 631.18 | 5,544,000 |
| 11 | 1/19/2012 | 319.3 | 319.3 | 314.55 | 637.82 | 12,657,800 |
| 12 | 1/20/2012 | 294.16 | 294.4 | 289.76 | 584.39 | 21,231,800 |
| 13 | 1/23/2012 | 291.91 | 293.23 | 290.49 | 583.92 | 6,851,300 |
| 14 | 1/24/2012 | 292.07 | 292.74 | 287.92 | 579.34 | 6,134,400 |
| 15 | 1/25/2012 | 287.68 | 288.27 | 282.13 | 567.93 | 10,012,700 |
| 16 | 1/26/2012 | 284.92 | 286.17 | 281.22 | 566.54 | 6,476,500 |
| 17 | 1/27/2012 | 284.32 | 289.08 | 283.6 | 578.39 | 7,262,000 |
| 18 | 1/30/2012 | 287.95 | 288.92 | 285.63 | 576.11 | 4,678,400 |

Table 1 represents the sample dataset of stock price with 1280 records. Here, the attributes are Open, High, Low, Close and Volume. Open is the price of stock on a date of opening. High is the stock price on a date which indicate highest price in a day. Low is the stock price on a date which indicate lowest price in a day. Close is the price of stock on a date of closing. Volume is the number of stocks purchased or traded on a day.

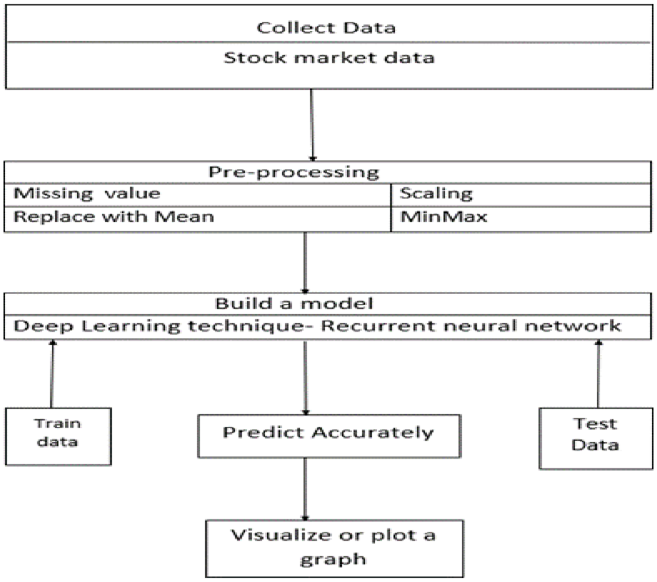


**Figure 3:** Architecture of Stock price prediction model

Below is the open and close price from 2012-2016 represented in graph. We can observe Open and Close price are coinciding from 2014 that means the stocks are not traded much, there is no business.

We propose a learning algorithm for predicting the end-of-day price of a given stock with the help of Long Short-Term Memory (LSTM), a type of Recurrent Neural Network (RNN). These predicted and analyzed data can be observed by an individual to know financial status of companies and their comparison. It also helps investors to invest in a stock at certain specific time with the help of analyzing past data by predicting for future stock prices. The main feature is to observe history of share market and generate patterns from large datasets, to predict an approximate value of share price. Its objective is to reduce vanishing gradient problem by support long-term strategies, so that history of trends is considered into account.

In this layer, the output produced by RNN layer is compared with the actual output if any error is there that will be reduced through back propagation in that in each iteration weights and bias values are adjusted the network and this process is repeated till the error in almost equal to zero. The architecture of stock price prediction model is shown in figure 3.

### 3.1 Data Pre-processing

The pre-processing stage is very important for producing quality results. Production data usually going to have missing values, Outliers, inconsistent data in the data set used for stock prediction we have done on of the data transformation technique such as transformation to perform this we have used MinMax Scaling. It will Transform any data sample in to the range between 0 and 1.

$$MinMax = (x - min(x))/max(x) - min(x) \quad (1)$$

### 3.1 Training Neural Network

In this phase, the data is fed to the LSTM network and trained with data set for forecast by providing biases and weights. Our LSTM model is composed of a sequential input layer followed by four LSTM layers with dropout layers and then finally a dense output layer with activation function. In this network for hidden layers sigmoid is used as activation function. For output layer we have used tanh as activation function.

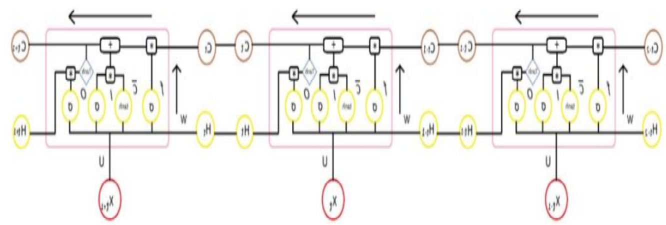

**Figure 4:** LSTM node structure at different time steps

LSTM is used to predict stock prices as it supports long term dependencies, which helps to predict stock price accurately. In figure 4, we are having LSTM node structure at different time steps In the below figure 5, we will explain how a single cell in LSTM works.

The below diagram describes single Cell in LSTM network

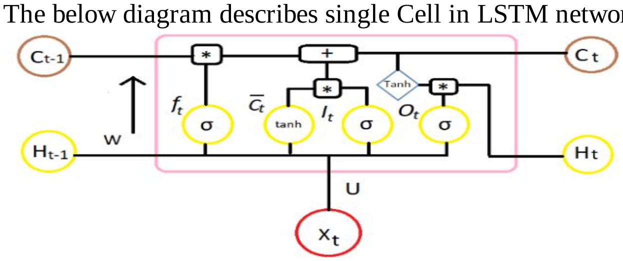


**Figure 5:** LSTM single Cell

A common LSTM unit consists of various gates which are used to controls flow between input gate and out put gate.

Input Gate:

The input gate is responsible for the addition of information to the cell state. This addition of information is basically three-step process as seen from the diagram above.

Regulating what values need to be added to the cell state by involving a sigmoid function. This is basically very similar to the forget gate and acts as a filter for all the information from h_t-1 and x_t.

Creating a vector containing all possible values that can be added (as perceived from h_t-1 and x_t) to the cell state. This is done using the tanh function, which outputs values from -1 to +1.

Multiplying the value of the regulatory filter (the sigmoid gate) to the created vector (the tanh function) and then adding

this useful information to the cell state via addition operation.
Forget Gate:
A forget gate is responsible for removing information from the cell state. The information that is no longer required for the LSTM to understand things or the information that is of less importance is removed via multiplication of a filter. This is required for optimizing the performance of the LSTM network.
Output Gate:
Not all information that runs along the cell state, is fit for being output at a certain time. This job of selecting useful information from the current cell state and showing it out as an output is done via the output gate.
The functioning of an output gate can again be broken down to three steps:
Creating a vector after applying tanh function to the cell state, thereby scaling the values to the range -1 to +1. Making a filter using the values of h_t-1 and x_t, such that it can regulate the values that need to be output from the vector created above. This filter again employs a sigmoid function.
Multiplying the value of this regulatory filter to the vector created in step 1, and sending it out as a output and also to the hidden state of the next cell.
The following are the equations use to compute different values at each node

$$f_t = \sigma(X_t * U_f + H_{t-1}*W_f) \quad (2)$$

First forgot gate take input vector Xt multiply with with U + previous hidden state multiply with with U and used sigmoid as activation function.

$$C_t = \tanh(X_t * U_c + H_{t-1}*W_c) \quad (3)$$

Current cell memory calculated using tanh activation function

$$t = \sigma(X_t * U_i + H_{t-1}*W_i) \quad (4)$$

input at specified time is calculated using above equation

$$O_t = \sigma(X_t * U_0 + H_{t-1}*W_0) \quad (5)$$

Out put at specified time is calculate using above equation

$$C_t = f_t * C_{t-1} + l_t * C_t \quad (6)$$

In above equation Memory state at given time t is calculated and it is forward to next time step

$$H_t = O_t * \tanh(C_t) \quad (7)$$

Current hidden state calculated using above equation using tanh activation function.
Notations used in above equation:
Xt = vector given as input, Ct-1 = Memory of previous Cell, Ct = Current Cell Memory, Ht = Output of Current Cell, W,U are weight vectors, Ht-1 = Output of previous Cell.

## 4. RESULTS AND DISCUSSION

We have build LSTM with four layers and passed various hyper parameters like drop out,regulation, Loss function mean square error with hundred epoch and batch size is 32 we got following results.
# Adding the first LSTM layer and some Dropout regularization//Sample LSTM node created using python.
regressor.add (LSTM (units = 50, return_sequences=True,13input_shape= (X_train. shape [1], 1))) regressor.add(Dropout(0.2))

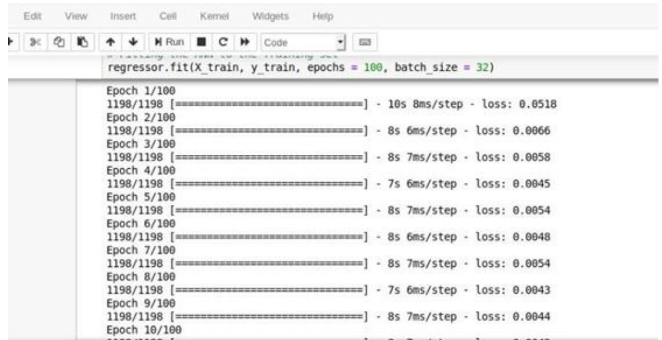


**Figure 6:** Loss value reduction in each epoch

The loss value for each epoch is shown in figure 6 and figure 7. From the figures, it is concluded that the loss gets reduced as the number of epochs increases.

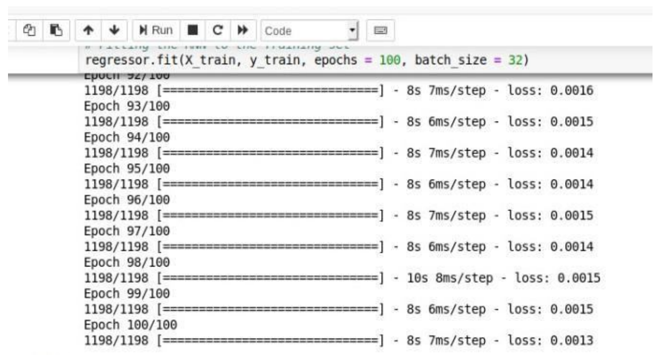


**Figure 7:** Loss value reduction in each epoch

At epoch 100 error rate is very less 0.0013 which is very less. So, we can stop iterating the model and it can be used for prediction of stocks.

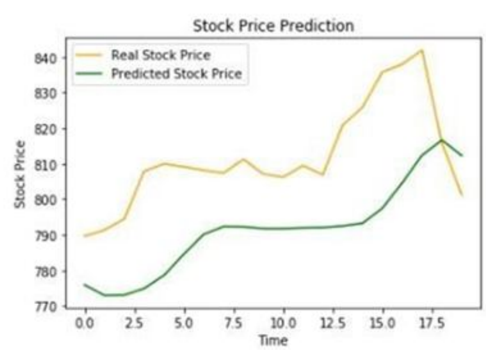


**Figure 8 :** Comparison between actual values and predicted values

The model is tested with the testing set and comparison between actual values and predicted values are plotted stock price we can able to see the graph shown in Figure 8.

## 5. CONCLUSION

In this paper we have implemented a model to predict price of the stock using RNN-LSTM simple dynamic neural network combined with functional expansion of the inputs is used to provide robust nonlinear framework for the prediction of time series databases like the stock market indices, currency exchange rates, and electricity price in a deregulated energy market. We have used tanh activation function in the output layer. Now, simple self-recurrent neural network using LSTM and keras is used to predict stock market more accurately.

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