Deep Learning based forecast using RNN for stock price prediction

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Abstract: Predicting the profit of a firm, predicting the expenditures and cost of an organization and predicting the demand of any product and service have always been playing a significant role in current global business scenario. For forecasting conventional techniques are being adopted. At the same time, accuracy is very important for forecasting. Thanks to the progress of technology, scientific techniques are replacing the conventional forecasting methods. Due to the phase of Industry 4.0, automation, artificial intelligence and machine learning have become areas of thrust and focus in the world. In this article, deep learning based recurring neural network technique that employs and recognizes sequential data is applied for prediction the stock price. Thanks to technological revolution, stock market analysis has become very easy and that too predicting stock price has become an important agenda for investors. Most of the stock and securities platforms have started using technological and scientific means and methods of price prediction and price analysis. Off late, machine learning algorithms have been evolved and customized for stock market analysis. Thus, this article has also applied deep learning technique for stock price prediction. The paper presents a well-organized approach that aids investors and organizations to gain profit.

Key Words: Machine Learning, Deep Learning, Artificial neural network, recurrent neural network, forecasting, stock price.

1.1 INTRODUCTION

Artificial Neural Networks have seen an explosion of interest over the last few years, and are being successfully applied across an extraordinary range of problem domains, in areas as diverse as finance, medicine, engineering, geology and physics. There are many attempts to formally define neural networks.**"**A neural network may be a system composed of the many simple processing elements operating in parallel whose function is decided by network structure, connection strengths, and therefore

It resembles the brain in two respects:

1. Knowledge is acquired by the network through a learning process.

2. Interneuron connection strengths known as synaptic weights are used to store the knowledge." -

"A neural network may be a circuit composed of a really sizable amount of straightforward processing elements that are neurally based. Each element operates only on local information. Furthermore each element operates asynchronously; thus there's no overall system clock." (Nigrin ,1993). Artificial neural systems, or neural networks, are physical cellular systems which may acquire, store, and utilize experiential knowledge (Zurada,1992)

Stock market remains one among the main means of investment for investors for a minimum of a few of decades. Accurate prediction of stock price movements is very challenging and significant topic for investors. Investors got to understand that stock price data is that the most essential information which is very volatile, non-linear, and non-parametric and are suffering from many uncertainties and interrelated economic and political factors across the globe. Deep learning algorithm - Recurrent Neural Networks (RNN) have been found to be an efficient tool in modelling stock prices and quite sizable amount of studies are done thereon . In this paper RNN modelling of stock prices of selected stocks under National Stock Exchange is attempted to predict closing prices. The network developed consists of an input layer, one hidden layer and an output layer and therefore the inputs being opening price, high, low, price and volume. Mean Absolute Percentage Error, Mean Absolute Deviation and Root Mean Square Error are used as indicators of performance of the networks. This paper is organized as follows. In the first section, the adaptability of RNN in stock prediction is discussed. Section two gives the literature review on the applications of RNNs in predicting the stock prices. Section three gives an overview of recurrent neural networks. Section four presents the methodology adopted. Section five gives the simulation and performance analysis. Last section concludes with future direction of the study.

1.2 STATEMENT OF PROBLEM:

The investors typically take the selections of shopping for or merchandising the stock by evaluating a company's performance and alternative surprising world, national & social events. Although, such events eventually have an effect on stock costs outright during a negative or positive method, these effects don't seem to be permanent most of the time. So, it's not viable to predict the stock costs and trends on the premise of basic analysis.

As a consequence an automatic system or model, to analyse the securities market and future stock trends supported historical costs and stock technical indicators, is needed.

Applying ancient machine learning and deep learning approaches yields average results because the securities market follows stochastic process motion. Applying Deep Learning algorithmic rule and adaptative to the stock technical indicators will create an efficient forecast. I created a trial to mix the thought and achieved higher results.

Most of the previous works haven't evaluated the algorithmic rule for prediction accuracy and suffer from over-fitting.

1.3 SCOPE OF THE STUDY:

In the case of prediction of assorted shares, there could also be some scope of specific business analysis. we are able to study completely dissimilar pattern of the share value of various sectors and may analyze a graph with a lot of different time span to fine tune the accuracy. This framework loosely helps in marketing research and prediction of growth of various corporations in numerous time spans. Incorporating alternative parameters (e.g. capitalist sentiment, election outcome, political science stability) that aren't directly correlative with the damage could improve the prediction accuracy.

1.4 RESEARCH GAP:

The literatures has predominantly used the Machine learning and neural network algorithms and tools like MATLAB, fuzzy interface system, generic algorithm, data mining algorithm, Leven berg-Marquardt, Scaled Conjugate Gradient ,Bayesian Regularization ,BIC, SER, deep learning, support vector machine, legendry neural network, VAR model approach, Stochastic time effective neural network, hybrid LSTM, wrapper-GA algorithm, harmony search algorithm, data clustering ,hybrid intelligence model, latent semantic indexing, financial econometrics, OSS training method, GDA method and backpropagation algorithm for prediction of stock model in various indexes and there is no literature on the prediction of stock price in the particular industry using deep learning. There square measure loads of difficult money indicators and additionally the fluctuation of the stock exchange is extremely violent. However, because the technology is obtaining advanced, the chance to realize a gentle fortune from the stock exchange is exaggerated and it additionally helps consultants to search the foremost informative indicators to create a stronger prediction. The prediction of the market price is of nice importance to assist in maximizing the profit of option purchase whereas keeping the chance low. Continual neural networks (RNN) have tested one among the foremost powerful models for process ordered information. In this paper, RNN introduces the memory cell, a unit of computation that replaces traditional artificial neurons in the hidden layer of the network. With these memory cells, networks are able to effectively associate memories and input remote in time, hence suit to grasp the structure of data dynamically over time with high prediction capacity. Thus this paper solves the problem of hidden layer complexities and the research is done in the IT industry using the NSE stock price of Tata Consultancy Services.

1.5 OBJECTIVESOF THE RESEARCH

1. To create a model to predict the future stock price using deep learning algorithm.
2. To determine the accuracy of this stimulation method.

2 LITERATURE REVIEW

TheliteraturereviewshowsthattherandomforestandSupportvectorregression for modelling the benefits of two stage prediction models over single stage prediction models, which becomes evident as the predictions are made for more number of days in advance. The best overall prediction performance isachieved by SVR–ANNmodel.(JigarPateletal.,2016).Derivedtheexactformulaforthe conversion option value of the European riskless convertible in the classical Black–Scholes–Merton framework. He argues it by Monte Carlo simulation that conversion option value estimates of the American risky convertible are located in a certain region defined by this formula. From estimates of the conversion probability, it is also shown that there exists an optimal reset time in the latter half of the trading interval (Toshikazu Kimura et al., 2018).The prediction based models where data is non-linear, whose patterns are difficult to be captured by traditionalmodels.TheyfocusedonAutoregressiveneuralnetwork,andGenetic algorithm for prediction of return of stock (Arun Agarwal et al., 2018). Implementation of a fusion model by combining the Hidden Markov Model (HMM), Artificial Neural Networks (ANN) and Genetic Algorithms -GA to forecastfinancialmarketbehaviour(MichaelKirley,2017).Thedeterminationof daily market prices and financial technical indicators are utilized as inputs to predict the one day future closing price of individual stocks. The prediction of stock price movement is generally considered to be a challenging and important task for financial time series analysis (Jonathan L. Ticknor,2018). A method of hybrid ANFIS model based on empirical mode decomposition for stock time series forecasting. It proposes a novel method and a simple approach for making stable predictions of fluctuating data (Liang-Ying Wei,2018). Proposal of a new hybrid model, based on four novel methods (CDPA, MEPA, RST and GA), to promote stock market forecasting performance (Ching-Hsue Cheng et al. 2018).

The Neural networks learning algorithms for stock market prediction based on tick data as well as 15-min data of an Indian company using Levenberg- Marquardt, Scaled Conjugate Gradient and BayesiaRegularization(Abishek Mishra et al.2019). Forecasting model by Combining nonlinear independent component analysis and neural network for the prediction of Asian stock market (Author WenshengDai , 2017). The forecasting performance of ARIMA and artificial neural networks model with published stock data obtained from New York Stock Exchange. The algorithm used for this modelling are BIC and SER (AyodeleAriyoAdebiyi,2016).Determinationofonecommonpatternamongthe stocks selected for trading –they exhibit high volatility and a short-term reversal return profile using machine learning and deep learning mechanisms (Thomas Fischer,2018).Evaluatingmultipleclassifiersforstockpricedirectionprediction byeenchmarkensemblemethods(RandomForest,AdaBoostandKernelFactory) against single classifier models -Neural Networks,Logistic Regression, Support VectorMachinesandK-NearestNeighbour(MichelBallings,2018).Examination ofFluctuationpredictionofstockmarketindexbyLegendreneuralnetworkwith randomtimestrengthfunction(AuthorFajiangLiu,2018).Forecastedchangesin Korea Composite Stock Price Index (KOSPI) using association rules facilitates effective investment decision making using VAR model approach (Sung Hoon Na,2017).

Fusionmodelbasedontheuseofmultiplediversebaseclassifiersthat oper- ate on a common input and a Meta classifier that learns from base classifiers' outputs to obtain more precise stock return and risk predictionswith the use of Wrapper-GA algorithm (Sasan Barak,2016). ANN based prediction model to improve the performance of prediction algorithms under dynamic conditions Kalman filter with the learning module performed better (4.41%–11.19%)thantheconventionalKalmanfilteralgorithmintermsoftherootmean squared error metric. (DoHyeun Kim,2018). Central idea to successful stock market prediction is achieving best results using minimum required input data and the least complex stock market model. The algorithms like Data clustering, Hybrid intelligence model are used for determining the output. (ArashGhanbari, 2017).

Evaluation of using two different representative stock market data (S&P500 and Korea Composite Stock Price Index 200 (KOSPI200)) and forecasted the framework with an overfitting prevention LSTM module and a prediction LSTM module .The ARIMA model is used for getting the desired result. (YujinBaek , 2018). LSI works to generate the prior knowledge of each learner. After the prior knowledge is raised, then one can predict learning style using the artificial neural network (ANN) method. (Lukito Edi Nugroho , 2018). Proposed a modelling and forecasting noisy realized volatility by using financial econometrics with a full correction of R2. An empirical example for S&P 500 data is used to demonstrate the techniques (Michael McAleer, 2016) and the networkwasabletopredictforNYSEeventhoughitwastrainedwithNSEdata. This was possible because both the stock markets share some common inner dynamics. The study of NSE Stock Market Prediction Using Deep-Learning Models.ThetoolsusedfortheresearchisLSTMnetwork.(HiranshaMetal.2017).

Proposed a novel stock prediction method based on the S-system model for Stock Market forecasting using restricted gene expression programming to forecast the stock market using hybrid intelligent algorithm.(Bin Yang et al.2018). Nifty stock index dataset where we predict the values on the basis of values from the past n days using Artificial Neural Network approach. The Backpropagation algorithm is used for obtaining the needed output. (Abhishek khar,2018).ThestockpricepredictionproblemasMarkovprocesswhichcanbe optimized by reinforcement learning based algorithm. TD (O), a reinforcement learning algorithm which leams only from experiences, is adopted and function approximation by artificial neural network is performed to leam the values of states each of which corresponds to a stock price trend at a given time. (Jae Wonidee,2018). The returns on the underlying asset and invokes the risk neutralityassumptiontoderivethevalueoftheoption.Techniquesforimproving theefficiencyofthemethodareintroducedusingMonteCarloalgorithm(Phelim P.Boyle,2017). Examined the potential of the Geometric Brownian Motion (GBM) method as an accurate and effective forecasting method compared to the Artificial Neural Network (ANN) method. The number of days the volatilityand drift are moved were also determined and this was used to perform the forecast of stock prices of holding companies registered with the Philippine Stock ExchangeandalsocomparedtotheANNmethod(ReneD.Estemberetal.2019). Enchanced Monte carlo estimates for american option price has been used for branching at the penultimate exercise point is certainly not required whenevera formula for pricing the corresponding European option is available using monte carloalgorithm(MarkBroadie et al. 2018). Sensitivity analysis for monte carlo simulationofoptionpricinghasconsideredbothEuropeanandAmericanoptions, starting with simple analytically tractable models to present the idea and proceeding to more complicated examples.An approach is proposed for the pricing of options with early exercise features by incorporating the gradient estimatesinaniterativestochasticapproximationalgorithm(Michaelc.Fu,2016).

The Robustness of Least-Squares Monte Carlo (LSM) for Pricing American Derivatives has been analysed and the impact of different basis functions on option prices are determined. The numerical results for American put options show that this approach is quite robust to the choice of basic functions.(Manuel Morenoetal.2016).DepictstheproblemofPricingcontinuousAsianOptionsby comparison of Monte Carlo and Laplace Transform Inversion Methods and correctingthediscretizationbiasinherentinsimulationwhenpricingcontinuous- time contracts, the use of suitably biased control variates . This approach is also comparedwiththeuseofRichardsonextrapolation. (DilipB.Madanetal,2017). Demonstrated how to incorporate optimal early exercise in Monte carlo method of valuing options by linking forward- moving simulation in the backward-moving recursion of dynamic programming through an iterative search process (Dwight Grant,2018)

2.2 HYPOTHESIS DEVELOPMENT:

This report will investigate a method of probability modelling using an approach called recurrent neural network. The following are the hypothesis for the study:

How can deep learning be used to model the probability of future stock returns?

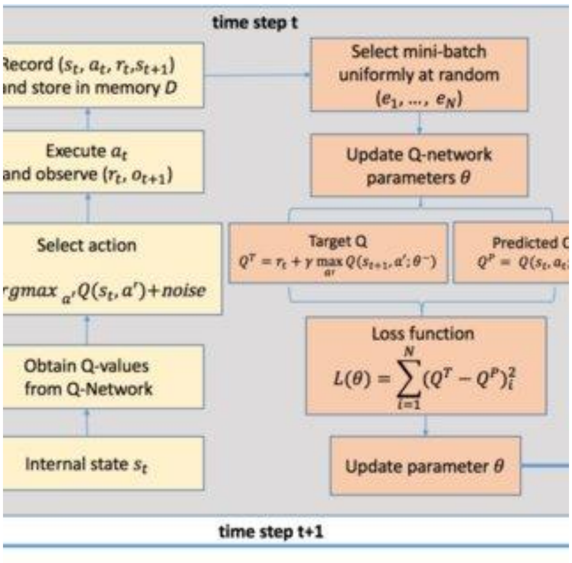
What is the accuracy of this simulation method?

3 RESEARCH METHODOLOGY

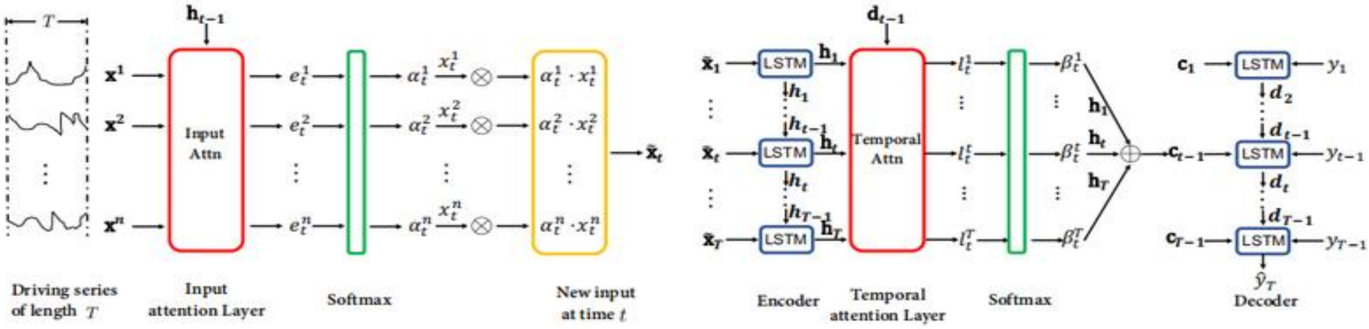
3.1 RESEARCH DESIGN:

The examined data consists of stocks from IT industry listed on the National Stock Exchange (NSE). The stocks were manually chosen based on their total volumeandtheirtrends.Forthisstudy,onlyhighvolumestockswithavarietyof positive and negative trends were selected. Volume was chosen as preference because I only wanted to analyze large-cap stocks. A variety of trends was preferred because I wanted to know whether the simulations work on both positive and negative trending stocks ornot. Using the historical data of the stock, the stimulation and modelling is done using recurrent neural network. The research has used the quantitative technique for the prediction of stock price.

Research type: Exploratory or predictive design



Source:*Arun Agarwal and V.N. Sastry, Recurrent neural network and a hybrid model for prediction of stock returns, Global finance journal, 2018, vol-9, doi:10.5430/gfj.v9n3p94.*



(a) Input Attention Mechanism (b) Temporal Attention Mechanism

Source: *Vineet Kumar and Abhishek Mishra, Indian stock market prediction using artificial neural networks on tick data, Journal of financial innovation, 2019, Vol-31(7), doi: 10.1191/23322039.2019.1534303*

The variables used for the research are Date, Open, High, Low, Close, Adj.Close and volume.

The following are the representation of variables.

Date – The date on which the stock is traded.

Open – The opening price of the stock on that particular day.

High - The highest price traded on that particular day.

Close – The closing price of the stock on that particular day.

Adj.Close – The adjustable closing price of the stock on that particular day.

Volume – The outstanding stock in the market on that particular day.

The returns are calculated and it is also used for analyzing of technical and fundamentals

3.2 SAMPLING DESIGN:

The 2321 days of stock price of TCS has been taken as the sample data and the part of the data is used as the test data and the trained data has been used for the stimulation of the model. The returns are calculated on the data set and it is used for fundamental analysis and technical analysis. Thus the sample design is based on the historical data and the sample is well tuned and the optimization is performed on the sample.

Algorithm:

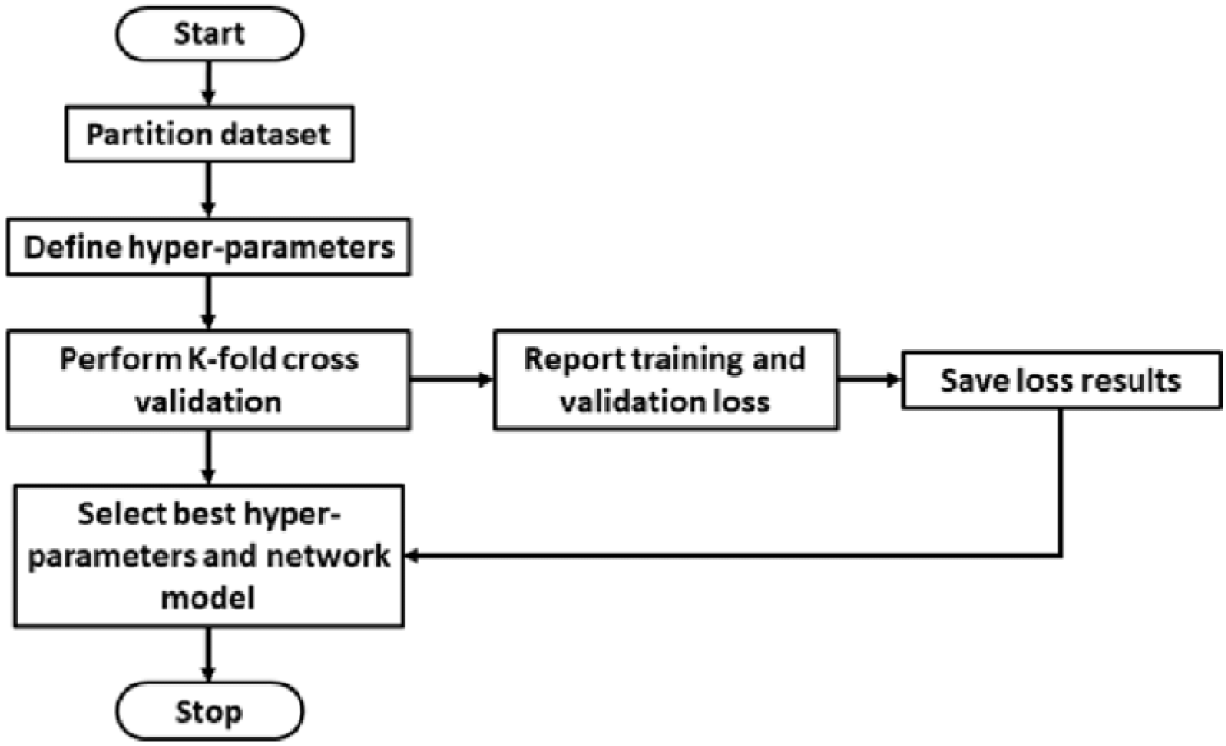
Input: Historical stock price data

Output: Prediction for stock prices data based on stock price variation.

1. Start
2. Stock data is taken and stored in a array of 3 dimensions (N,W,F) Where
   N is number of training sequences W is sequence length
   F is number of feature of each sequence
3. A network structure is built with [1,a,b] Where

1-Inputlayer,aneuronsinthenextlayer,bneuroninthesubsequentlayer, and a single layer with a linear activationfunction.

4. Train the constructed network ondata
5. Use the output of the last layer as prediction of the next timestep.
6. Repeat step 4 and 5 until optimal convergence isreached.
7. Output prediction by providing test data ad input to thenetwork.
8. Evaluate accuracy by comparing predictions made with actualdata.
9. End



3.3 DATA COLLECTION METHOD:

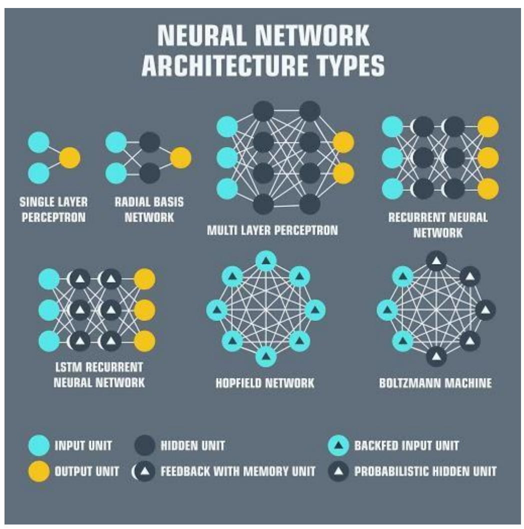
The secondary data collection technique is used for research

Secondary data collection:

For this research, the data was collected from the website of national stock exchange. The data has been collected have a span of 6 years, 01-12-2014 to 01-12-2019. This span was chosen to allow 5 years of historical pricestobeusedforcalculatingstatisticalvalues.Thelastyearofhistoricalprices was used as a reference for comparing the simulated and actual prices. The span includes daily data and since not all days are banking days, only 1231 days of data were data were collected. These data are used for simulation and modelling using deep learning algorithm

3.4 STATISTICAL TOOLS USED:

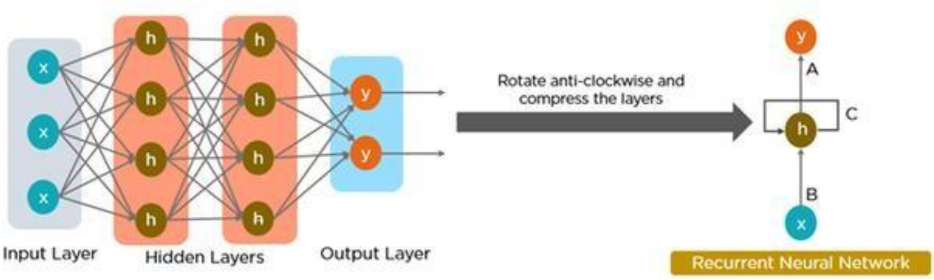
Artificial Neural Network



Source: *Toshikazu Kimura,Toshio Shinohara, Monte Carlo analysis of convertible bonds with reset clauses, Journal of multinational financial management,2018,vol-63, doi: 10.2458/jmfm.v63.n5.4841*

Recurrent Neural Network

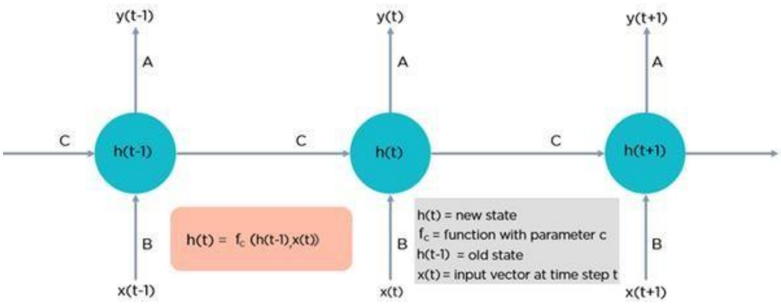
RNN, normally referred to as perennial Neural Network could be a very fashionable Deep Learning model that is employed to hold out variety of Deep Learning tasks like Time Series prediction, Image Captioning, Google motorcar complete feature, etc.RNN because the name suggests, uses formula technique to make models. It is completely dissimilar from a Feed Forward Neural Network wherever the data solely flows in forward direction. But in RNN, there's iteration of data. Here is however a perennial Neural Network appearance like:



Source: *Thomas Fischer , Deep learning with long short-term memory networks for financial market predictions, Journal of Computational Intelligence and Information management ,2018, Vol-63(8), doi:10.1080/154049.2018.1564535*

In the higher than diagram, x is that the input, h is that the hidden state values and y is that the foreseen output. Here A, B and C area unit parameters of the network.

In RNN, the input at a selected time stamp (t) is that the current input at time t also because the output of the previous hidden state i.e. h(t-1). There's invariably a iteration of inputs at terribly time stamp. Hence, it's known as a continual Neural Network. Below diagram shows how an open RNN looks like:



Source: *Thomas Fischer , Deep learning with long short-term memory networks for financial market predictions, Journal of Computational Intelligence and Information management ,2018, Vol-63(8), doi:10.1080/154049.2018.1564535*

We can see clearly, at each time stamp, the previous hidden state worth is fed as input to this state. Recurrent Neural Networks area unit of varied types:
1. **One to 1** - Here we've got single input and single output. This can be popularly referred to as a Vanilla Neural Network.
2. **One to Many** - Here we've got single input and multiple outputs. a decent example wherever one to several RNN is employed is for Image Captioning.
3. **Many to 1** - Here we've got multiple inputs and single output. An example of this might be sentiment prediction.
4. **Many to Many** - Here we've got multiple inputs moreover as outputs.
Machine translation is on such example wherever you admit defeat a sequence of inputs in one language and it generates your output in numerous languages. RNN's have the power to hit the books previous inputs as a result of its internal memory and thence, area unit wont to solve future Dependencies via LSTMs. this can be one in every of the explanations why RNN's area unit utilized in Google's Autocomplete feature.
Another huge advantage of RNN in Deep Learning is that it will handle sequent knowledge. Therefore, RNN's area unit typically used for Time-Series Prediction.
Advantages of Recurrent Neural Network are as follows:
1. AN RNN remembers every and each data through time. it's helpful in statistic prediction solely as a result of the feature to recollect previous inputs moreover.
2.perennial neural network area unit even used with convolutional layers to increase the effective constituent neighborhood. The paper involves the higher than deep learning algorithmic rule for standardization of the sample knowledge. The Rstudio is employed for implementing RNN algorithmic rule mistreatment R programming.

4 ANALYSIS AND DISCUSSIONS

The analysis is done using deep learning algorithm by focusing on more accuracy on stock price.R is for statistical computation. It is well-suited to do computationally heavy financial analysis. In particular, evaluating performance of trading rule based on technical indicators and the historical data are used for modelling.

Output :

```
Stock<-  read.csv  (file.choose  (),  header  =  T)
setwd("G:/Project_Analysis")
class(Stock)
dim(Stock)
nrow(Stock)
ncol(Stock)
names(Stock)
str(Stock)
```

```
> class(Stock)
[1] "data.frame"
> dim(Stock)
[1] 1230    7
> nrow(Stock)
[1] 1230
> ncol(Stock)
[1] 7
> names(Stock)
[1] "Date"      "Open"      "High"      "Low"       "Close"     "Adj.Close"
[7] "Volume"
> str(Stock)
'data.frame':   1230 obs. of  7 variables:
 $ Date     : Factor w/ 1230 levels "01-01-2015","01-01-2016",..: 37 74 114 154 196 320
 364 404 444 484 ...
 $ Open     : num  1325 1346 1336 1332 1320 ...
 $ High     : num  1350 1355 1337 1334 1325 ...
 $ Low      : num  1323 1325 1309 1315 1286 ...
 $ Close    : num  1346 1329 1318 1319 1289 ...
 $ Adj.Close: num  1167 1152 1142 1143 1118 ...
 $ Volume   : int  1896354 1436572 3094670 1285308 2359676 3232574 2487940 2087970 1938
822 2380786 ...
```

INTERPRETATION:

The dataset consists of 7 variable namely Date, Open. High, Low, Close, Adj.Close and volume with 1230 rows as observations and all the data in the dataset are numeric.

head(Stock)

```
> head(Stock)
        Date    Open    High     Low   Close Adj.Close  Volume
1 01-12-2014 1325.25 1350.00 1322.62 1346.47  1167.033 1896354
2 02-12-2014 1346.50 1355.47 1324.68 1328.65  1151.588 1436572
3 03-12-2014 1335.95 1336.70 1309.25 1317.68  1142.080 3094670
4 04-12-2014 1332.00 1333.50 1314.95 1318.97  1143.198 1285308
5 05-12-2014 1320.45 1324.90 1286.07 1289.47  1117.629 2359676
6 08-12-2014 1297.50 1297.50 1250.82 1256.40  1088.967 3232574
```

tail(Stock)

```
> tail(Stock)
           Date    Open    High     Low   Close Adj.Close  Volume
1225 22-11-2019 2097.00 2107.00 2060.50 2071.70   2071.70 3742049
1226 25-11-2019 2074.55 2084.95 2052.20 2081.50   2081.50 2737010
1227 26-11-2019 2089.85 2097.90 2035.05 2046.65   2046.65 6561580
1228 27-11-2019 2052.00 2071.70 2046.55 2054.30   2054.30 2907521
1229 28-11-2019 2067.05 2094.40 2060.00 2077.35   2077.35 2924429
1230 29-11-2019 2085.00 2085.00 2045.80 2053.25   2053.25 2064271
```

INTERPRETATION:

The top 6 observations and bottom 6 observations of the variables Date, Open, High, Low, close and volume are shown as sample data in the output. And the above output shows that the variables Date, Open, High, Low, Close, and Adj.Close are in numeric data type and volume is integer data type.

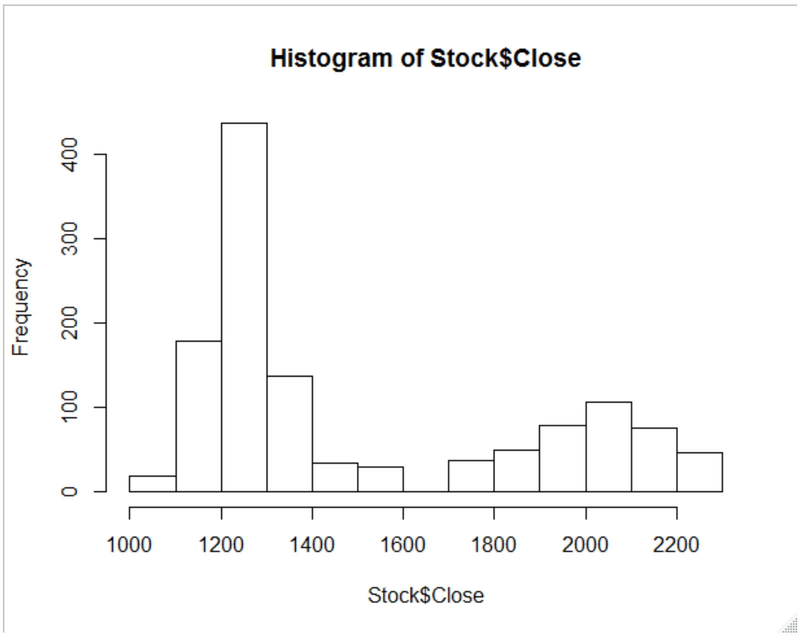
INTERPRETATION :

The above graph shows that the stock price of the company has decline over years till 2018 and it has fluctuation in the year 2018 – 2019.

INTERPRETATION:

The Bollinger band if used as the technical indicator for stock price. The above graph clearly shows that the stock price is going to incline in the upcoming years and it is the right time to buy because the Bollinger band is very low and the technical indicator shows an uptrend.

hist(Stock$Close)



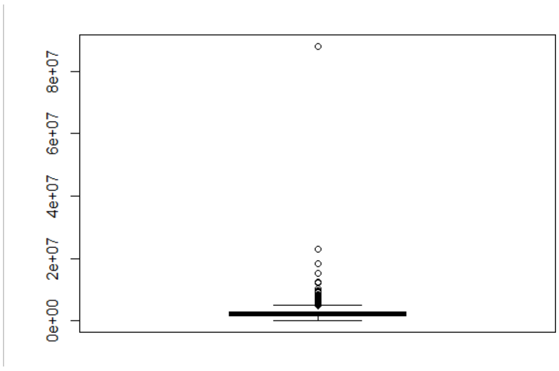
INTERPRETATION:

The above histogram of closing price shows that the most of the closing price of the TCS stock was in the range of 1200 to 1300 with the high frequency of more than 400 times

par(Stock=c(1,2))

boxplot(Stock$Close)

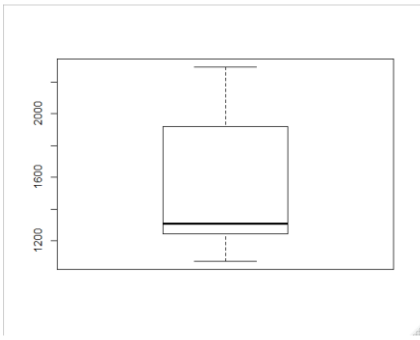
boxplot (Stock$Volume)



INTERPRETATION:

The above boxplot shows the outliers present in the dataset. The most of the outliers are present in the dataset for the volume with the value of above 1800000 and most of the volume was in the range of 1000000

par(Stock=c(1,2))



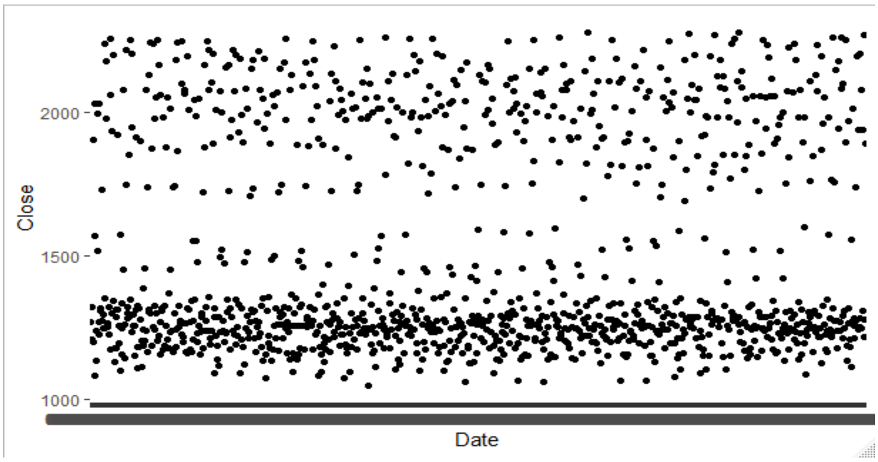
boxplot(Stock$Low)

boxplot (Stock$High)

INTERPRETATION:

The most of the low price lies in the range of 1300 and the lowest value traded in the past 5 years is 1025 and it has gone above 2300.

ggplot(data = Stock)+geom_point(mapping = aes(x=Date, y= Close))



INTERPRETATION:

The above plot determines that there is high fluctuation at the price of 1200 to 1400 and the TCS stock closed at the range of 1400 to 1800 was very less

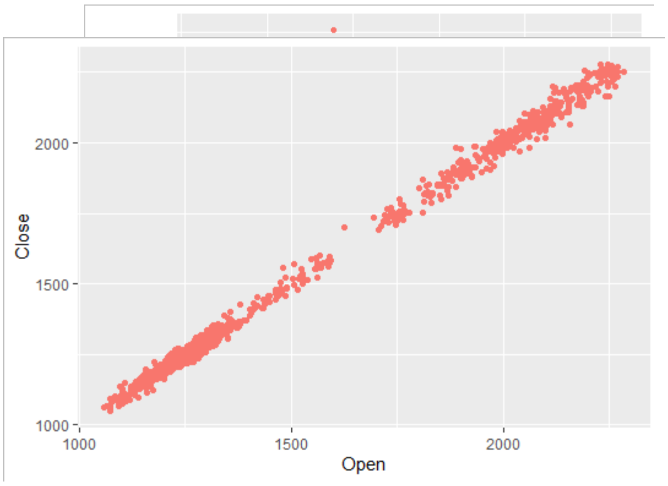
ggplot(data = Stock)+geom_point(mapping = aes(x=Volume, y= Close))

```
fancy_scientific<- function(l)
 {
# turn in to character string in scientific notation
 l <- format(l, scientific = TRUE)
# quote the part before the exponent to keep all the digits
l <- gsub("^(.*)e", "'\\1'e", l)
# turn the 'e+' into plotmath format
l <- gsub("e", "%*%10^", l) # return
this as an expression parse(text=l)
  }
ggplot(data = Stock)+geom_point(mapping = aes(x=High, y= Low ))
ggplot(data=Stock)+geom_point(mapping=aes(x=Close,y=Volume,shape="Retangle",colour="red"))+scale_y_
continuous (labels=fancy_scientific)
```

INTERPRETATION:

The above graph interprets the relationship between closing price and volume. When the volume increases the closing price also increases and when the volume decreases the closing price also decreases. This is due to change in demand and supply.

ggplot(data=Stock)+geom_point(mapping=aes(x=Open,y=Close,shape="Rectangle",
colour="red"))

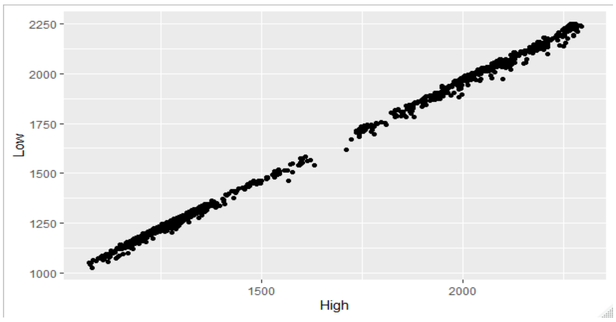


INTERPRETATION:

The above graph represents the relationship between the opening price and the closing price of the stock. The plot clearly depicts the linear movement between the opening and closing price on the particular day. Though there were some fluctuations, whenever there is inclination in the opening price, the closing price also increases on that particular day and vice versa for declination of the stock price.

#Factes splits the plot into subplots that each display one subset of the data

ggplot(data=Stock)+geom_point(mapping=aes(x=Close,y=Open))+facet_wrap(~Stock$High,nrow=2)



INTERPRETATION:

The above clearly shows the relationship between the high and low price on the particular day. The fluctuation is high in the range of 1100 to1400 and in the range of 1750 to 2000. This fluctuation is due to the change is the volume of demand and supply of that particular day. The fluctuation may also be due to some change in fundamentals.

STATISTICAL ANALYSIS

Statistics	***Closing price of the stock***	***Return of the stock***
Mean	**1503.699**	**0.045535269**

Median	**1292.45**	**0.02932922**
Mode	**1256.9**	**0**
Standard Deviation	**372.009**	**1.421307722**

INTERPRETATION:

The above statistics shows that the average stock price of TCS in past five years is 1503.699 and its mean of return is 0.045 with the standard deviation of 1.42. This shows that there may be an increase or decrease of Rs.372 in the closing price of the stock from the mean value. The frequency of occurrence of 1256.9 is high. This shows that most of the time TCS stock has been closed at Rs.1256.9.

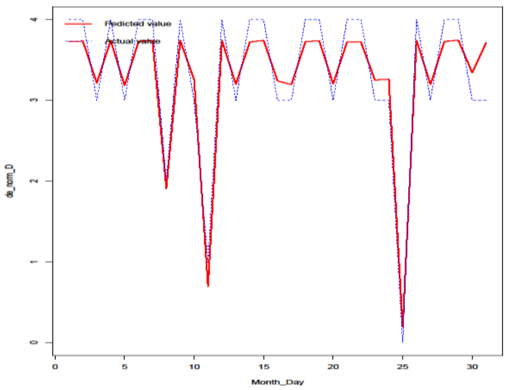
RNN Algorithm	
R-Square Value	0.913
Absolute error rate	0.16
Epoch	40
Hidden Note	12
Learning Rate	0.09

INTERPRETATION:

The R-square value determines that the model has high level of accuracy with 91.6% with the minimal absolute error rate of 0.16. In machine learning and statistics, the learning rate is a tuning parameter in an optimization algorithm that determines the step size at each iteration while moving toward a minimum of a loss function. The 40 epoch of used in the model for tuning of data with 12 hidden node and the learning rate of 0.09. This proves that the model is highly accurate.

PREDICTION OF STOCK PRICE:

The following is the output of the TCS stocks using deep learning algorithm



INTERPRETATION:

The above graph predicts the value of stock after 1 year by analyzing the historical data, fundamentals and technical. The stock price varies with increase and decrease in demand and supply. If the demand increases, the stock price also increases and if the demand decreases, the stock price also decreases. The model has compared the variation of actual price of the stock and the predicted price of the stock. The x axis determines the days of the month from day 1 to day 30. The TCS stock price is predicted to be decline highly using the day 10 and 25 of the month. It is recommended to buy the stock by taking long position during that period and the stock can be sold at the end of the year to get the high return.

4.1 IMPLICATIONS OF THE RESEARCH:

1. The model is created using the deep learning algorithm for the prediction of stock price using the historical stock price, fundamental and technical analysis.

2. The model highly accurate with R-Square value as 0.913, hidden node as 12 and learning rate as 0.09) and very minimal absolute error rate of 0.16 and 40 epoch are used for modelling. The quantitative value proves that the model is highly tuned.

3. As an outcome the model predicts the long market trends of the large capitalization stocks. The time period in which the predicted trends almost follow actual trend is considered better for future investments. However, the uncertain trends justify that there might be risk involved with particular stock for particular time

4. Thus this model can be used by the various large cap companies from various industry

4.2 LIMITATIONS OF THE RESEARCH:

1.The must need large dataset for prediction.

2. The model is tested only for stocks with large capitalization.

4.3 FUTURE SCOPE OF THE RESEARCH:

The above research work was carried out using deep learning technique and R language was applied to get the output. The study may be extended by further validating the results using some other language. A comparative justification may also be made and subsequent errors in forecasting may be minimized.

5CONCLUSION:

The efficiency was inspected by applying technical analysis to the stock prices and the concept of deep learning algorithms has been demonstrated. The model presents a well-organized approach that aids investors and organizations to gain profit. Optimal recurrent neural network algorithm presents decision based indicator (Price-rise (1) or Price-fall (0)) as well as trend based analysis. The proposed Optimal Deep Learning Approach is a market independent approach as it is discovering the potential indicators existing in the data and applying RNN of deep learning rather than fixing data or model. This work opens several research confronts to get more insights on stock trends forecasting. In future the research work can be extended by tuning the algorithm for small capitalization stocks. The proposed model can be further evaluated and optimized for stock indices. The proposed deep learning algorithm can also be further enhanced to optimize the performance. To support investors, the proposed model can be further integrated into an automated system for trading on specific stocks.

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