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Stock Market prediction based on Stock Prices and Tweets using Deep Neural Network

Dr.P.Boobalan , Bandana Raji , Satish.S
, Thamizharan.G
Department of Information Technology
Puducherry Technological University
Puducherry, India
boobalanp@pec.edu

Abstract-- **Stock Market Analysis and Prediction (SMAP) is a web based application able to predict the stock prices such as close, open, high anf low of companies based on their market values and news sentiments surrounding the company. It is a portal where, general stock market enthusiast can keep track of their invested companies and are also able to instantly contact their brokers for purchase or sales of the stocks. The main application of this system however would be to predict the market values. Along with that it has the features of news portal. Deep Neural Network (DNN), used for stock market analysis and prediction. The algorithm's main goal is to learn the market trends by training with the past data and predicting the future value. The calculated values of the computational analysis i.e. prediction is used to display nearly accurate result.**

Keywords--- Stock market, SMAP, LSTM, RNN,DNN

I. Introduction

Stock analysis is the evaluation of a particular trading instrument, an investment sector, or the market as a whole. Stock analysts attempt to determine the future activity of an instrument, sector, or market [1] . Stock market prediction is the act of trying to determine the future value of a company stock or other financial instrument traded on an exchange. The successful prediction of a stock's future price could yield significant profit. The project entitled "Stock market Prediction and Analysis " is the web based application. It predict or forecast the future of stock market based on historical time series data. NEPSE historical time series data were scraped using scrapy tools and stored. Machine learning models for time series forecasting were used to train those historical data and the result is visualized on web page for easy understanding and analysis of stock market. The project encompasses the concept of Data mining and Statistics which makes heavy uses of NumPY, Pandas and data visualization libraries for data processing. In short, the system accept the historical data set of company which is processed on our local server and result is displayed on web browser. Since it is a web application, can be accessible to everybody through the medium of internet when it is live or hosted on particular domain.

The project is targeted to companies where stock is traded in order to predict and analysis the financial status and future of company. Along with companies general individual to understand the pattern of stock market and invest the money. The Closing Value is the price at which the most recent trade occurred. When the stock market is open -- the Nepal Stock Exchange is open Sunday through Friday 11:00 a.m. to 15:00 p.m. and are closed on public holidays -- the closing value provides the most up-to- date value of a stock. Odd lot trading is done on Fridays. Once the stock market closes, the closing price is the best gauge of value until the stock market opens the next business day. 2 1.2 Problem Statement Stock Market Prediction for continuous seven days using Deep Neural Network.

II. Literature Survey

The review of literature is without a doubt incomplete with Burton G. Malkiel's theory of Random walk of stock market. According to the author stock market moves in a random fashion and any kind of previous or historical data cannot be used to predict its future values. According to the author the market is efficient and will remove any kind of bias or patterns. But we will observe that many research has provided enough evidence that such prediction not only works but beats the traditional methods by a long shot[2].

Aishwarya Singh forecast on time series data using time series analysis models. She have implemented different models like MA, AR, DNN, LSTM etc. According to her LSTM is best for large number of data and DNN is suitable for less (avg 800) data[3].

Hirotaka Mizuno, Michitaka Kosaka, Hiroshi Yajima demonstrated the use of artificial neural network on TOPIX (Tokyo Stock Exchange Prices Index). They used moving average, Deviation of price from moving average, Psychological line, Relative strength index as inputs for the ANN. Output of the ANN was buy, hold and sell signals. Their results demonstrated their system could achieve from 9-10% of average return, which was lower than traditional buy and hold strategy. However Marijana Zekic has pointed out that many author ignore the possible structure of ANN which could benefit certain situations. The demonstrates that certain type of ANN structure perform better than others like 10-20-1 structure with back propagation Learning[4].

FernandoFernández-Rodríguez,Christian González-Martel,Simón Sosvilla-Rivero has demonstrated the correctprofitability in different phases of market (bullish, bearish and neutral. Their work demonstrates that technical analyses performs far better than buy and hold strategy in different market conditions. Discrete Wavelet Transform (DWT) and Artificial Neural Network (ANN) for predicting financial time series has been studied by S. Kumar Chandar, M. Sumathi and S. N. Sivanandam. Their hybrid forecasting technique has achieved better results compared with the approach which is not using the wavelet transform.

III. Implementation

Themainpurposeofimplementationofthissystemistopredictthestockpricesbasedonthe previous stock prices.

a. AlgorithmDesign

Algorithmsaretheoperationalinfrastructureofeveryproject;thealgorithmsdeterminehowa ndhowtheprogramoperatedandgeneratedresultsbasedonthecalculations.Aneffectivealgorithmm ustencompassallthedatavariablesavailableforcomputationandinreturngenerateanefficientflowas wellastrueresultsoftheprocessingafterwards..Whenit comes to predictiveanalysisthere is a myriaofhoicesovertheinternetthatoperateinstatisticaldatatogenerateassociativeoutput.Choosing betweenthesenumerousalgorithmsitselfneedsagoodamountofstudyuponthetopicsandalsoadeepa nalysisofthe predictions being made from the system.Since, in this casetherearemultiplenumber ofdependentvariablesthatarekeypointsonprediction,wehaveadoptedthealgorithmofDNN .

b. DataCollection

Inthefirstphase,anumberofscrapingscriptstocollectdatafromthesourcesmentionedprevio uslyin the project.Thedata is composedof market dataofcompanies and dependent varaibles.

In the problem, each record of data set includes daily information which consists of the closing price, the highest price, the lowest price, and the opening price named at day t as x(t), xh(t), xl(t) and xo(t) respectively. Other technical analysis parameters used as input include the leading, lagging and trend change indicators to get a composite result.

This paper uses 25 variables for forecasting as used in literature survey. The variables I1 to I25 are computed based on the equations in Table 1. However, two parameters have been replaced with Bollinger Bands which compare the volatility and the relative price levels . These variables when used as input to the model provide the forecast for the closing price on the next day. The forecast is for short-term because data far from the forecasting date provides less and less information useful to forecasting value

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	Date	Open	High	Low	Close	Adj Close	Volume
2	20-04-2020	1271	1281.6	1261.37	1266.61	1266.61	1695500
3	21-04-2020	1247	1254.27	1209.71	1216.34	1216.34	2153000
4	22-04-2020	1245.54	1285.613	1242	1263.21	1263.21	2092400
5	23-04-2020	1271.55	1293.3101	1265.67	1276.3101	1276.3101	1566200
6	24-04-2020	1261.17	1280.4	1249.45	1279.3101	1279.3101	1630600
7	27-04-2020	1296	1296.15	1269	1275.88	1275.88	1600600
8	28-04-2020	1287.9301	1288.05	1232.2	1233.67	1233.67	2951300
9	29-04-2020	1341.46	1359.99	1325.34	1341.48	1341.48	3793600
10	30-04-2020	1324.88	1352.8199	1322.49	1348.66	1348.66	2668900
11	01-05-2020	1328.5	1352.0699	1311	1320.61	1320.61	2072500
12	04-05-2020	1308.23	1327.66	1299	1326.8	1326.8	1504000
13	05-05-2020	1337.92	1373.9399	1337.46	1351.11	1351.11	1651500
14	06-05-2020	1361.6899	1371.12	1347.29	1347.3	1347.3	1215400
15	07-05-2020	1365.9399	1377.6	1355.27	1372.5601	1372.5601	1397600
16	08-05-2020	1383.13	1398.76	1375.48	1388.37	1388.37	1386900
17	11-05-2020	1378.28	1416.53	1377.152	1403.26	1403.26	1412100
18	12-05-2020	1407.12	1415	1374.77	1375.74	1375.74	1390600
19	13-05-2020	1377.05	1385.4821	1328.4	1349.33	1349.33	1812600
20	14-05-2020	1335.02	1357.42	1323.91	1356.13	1356.13	1603100
21	15-05-2020	1350	1374.48	1339	1373.1899	1373.1899	1707700
22	18-05-2020	1361.75	1392.325	1354.25	1383.9399	1383.9399	1822400
23	19-05-2020	1386.9969	1392	1373.485	1373.485	1373.485	1280600
24	20-05-2020	1389.58	1410.42	1387.25	1406.72	1406.72	1655400
25	21-05-2020	1408	1415.49	1393.45	1402.8	1402.8	1385000
26	22-05-2020	1396.71	1412.76	1391.83	1410.42	1410.42	1309400
27	26-05-2020	1437.27	1441	1412.13	1417.02	1417.02	2060600
28	27-05-2020	1417.25	1421.74	1391.29	1417.84	1417.84	1685800
29	28-05-2020	1396.86	1440.84	1396	1416.73	1416.73	1692200
30	29-05-2020	1416.9399	1432.5699	1413.35	1428.92	1428.92	1820900

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Figure 1. Company Stock Data

Name of the Variables	**Description and Formula**
I1 = xo(t)	Open Price
I2 = xh(t)	High Price
I3 = xl(t)	Low Price
I4 = x(t)	Close Price
I5 = MA5, I6 = MA10, I7 = MA20	Moving Average
I8 = BIAS5, I9 = BIAS10 I10 = DIFF	BIAS EMA12-EMA26
I11=BU	(x(t)-bollingerupper)/bollingerupper

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I12 = BL	(x(t)-bollingerlower)/bollingerlower
I13 = K, I14 = D	Stochastic Fast %K ,Fast %D
I15 = ROC	Price rate of change
I16 = TR	True range of price movements
I17 = MTM6, I18 = MTM12	Momentum
I19 = WR%10, I20 = WR%5	Williams index
I21 = OSC6, I22 = OSC12	Oscillator
I23 = RSI6, I24 = RSI12	Relative strength index
I25 = PSY	Psychological line

Table 1. Technical Indicators

c. DNN Model

Oneof themost common methods used in time seriesforecastingis knownas theDNNmodel,whichstandsfor Deep Neural Network.DNNisamodelthatcanbefittedtotimeseriesdatainordertobetterunderstandorpredictfuturepointsintheseries.Therearethreedistinctintegers(p,d,q)thatareusedtoparametrizeDNNmodels.Becauseofthat,DNNmodelsaredenotedwiththenotationDNN(p,d,q).Togetherthesethree parameters account forseasonality, trend, and noisein datasets:

- pisthe*auto-regressive*partofthemodel.Itallowsustoincorporatetheeffectofpastvaluesintoourmodel.Intuitively, thiswouldbesimilartostatingthatitislikelytobewarmtomorrow ifit hasbeenwarm the past 3 days.
- disthe*integrated*partofthemodel.Thisincludestermsinthemodelthatincorporatetheamountofdifferencing(i.e.thenumberofpasttimepointstosubtractfromthecurrentvalue)toapplytothetimeseries. Intuitively,thiswouldbesimilartostatingthatitislikelytobesametemperaturetomorrowifthe differenceintemperatureinthelastthreedayshasbeen verysmall.

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- q is the*movingaverage* part ofthe model.This allows us to setthe error of our model as alinearcombination oftheerror values observedatprevious time points in the past.

Equations

Theequation ofDNN(2,0,1) is like:

Yt = a1Yt-1+a2Yt-2+b1Et-1 whereAR term=a1Yt-1+ a2Yt-2and MAterm = b1Et-1

Inourprojectyistheobservedvalueofdifferenttimestamptofstockandvalueofp,d,qis provided as per necessary to obtain high accuracy.
The algorithm is implemented on following order:

Step1:CheckStationary:- If atimeserieshasatrendorseasonalitycomponent,itmustbemadestationarybeforewe can useDNNto forecast.
Step2:Difference:- Ifthetimeseriesisnotstationary,itneedstobestationarizedthroughdifferencing.Takethefirstdifference,thencheckforstationarity.Takeasmanydifferencesasittakes.Makesureyoucheckseasonaldifferencingaswell.

Ifd=0:yt =Yt

Ifd=1:yt =Yt -Yt-1

Ifd=2:yt = (Yt -Yt-1)-(Yt-1 – Yt-2)=Yt -2Yt-1 +Yt-2

Here,y tis the differencedvaluethat is calculatedto make the datastationary.
Step3:-Filter out avalidation sample:-Thiswillbeusedtovalidatehowaccurateourmodel is. Usetraintestvalidation split to achievethis.
Step4:-SelectARandMAterms:-UsetheACFandPACF todecidewhethertoincludeanAR term(s), MAterm(s),or both.
Step 5:- Build amodel:Build the model to fit.
Step6—Validatemodel:-Comparethepredictedvaluestotheactualinthevalidation sample.
Step 7:- Calculate RMSEorMAPE of predictionto checkaccuracy.

So,wehavetodealwitheithertrendorseasonal.Whendealingwithseasonaleffects,wemakeuseofthe*seasonal*DNN,whichisdenotedasDNN(p,d,q)(P,D,Q)s.Here,(p, d,q)arethenon-seasonalparametersdescribedabove,while(P,D,Q)followthesamedefinitionbutareappliedtotheseasonalcomponentofthetimeseries.Thetermsistheperiodicityof thetime series (4

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forquarterlyperiods,12
foryearlyperiods,etc.).ParameterSelectionfortheDNNTimeSeriesModel,lookingtofittimeseriesdatawithaDNNmodel,ourfirstgoalistofindthevaluesofDNN(p,d,q)thatoptimizeametricofinterest.Inthissection,wewillresolvethisissuebywritingPythoncodetoprogrammaticallyselecttheoptimalparametervaluesforourDNN(p,d,q)timeseriesmodel.Alongwiththoseparametersweuse*CLOSING*valueofthetimeseriesstockdataas a featureto predict thefuture value.Similar, incase of seasonalDNN. Weuseda"gridsearch"toiterativelyexploredifferentcombinationsofparameters.Foreachcombinationofparameters,wefitanewDNNmodelwiththeSDNNX()functionfromthestatsmodelsandassessitsoverallquality.Oncewehaveexploredtheentirelandscapeofparameters,ouroptimalsetofparameterswillbetheonethatyieldsthebestperformanceforourcriteriaofinterest.InStatisticsandMachineLearning,thisprocessisknownasgridsearch(orhyperparameteroptimization)formodelselection.Whenevaluatingandcomparingstatisticalmodelsfittedwithdifferentparameters,eachcanberankedagainstoneanotherbasedonhowwellitfitsthedataoritsabilitytoaccuratelypredict futuredata points.

WewilluseMAPEorRMSEerrorcalculationmechanism,whichisconvenientlyreturnedwith DNNmodelsfittedusingstatsmodels.TheMAPEmeasureshowwellamodelfitsthedatawhiletakingintoaccounttheoverallcomplexityofthemodelsameincaseofRMSE.Amodelthatfitsthedataverywell whileusinglotsoffeatureswillbeassignedalowerMAPEscorethanamodelthatusesfewerfeaturestoachievethesamegoodness-of-fit.Therefore,weareinterestedinfindingthemodelthatyields thelowest MAPEvalueorRMSE.TheDNNorderandseasonalorderwithlowestMAPEvalueisusedwithSDNNXmodelforseasonalcasebutonlyDNNorderfortrendcasetofitandpredictthe futurevaluepassinghistoryvaluetogether.Alongwiththeplotforpredictionwewillplotdiagnonticsplotstoensurenonoftheassumptionsmade bymodel are violates.This section will shed some light on our proposed approach to predict the short-term stock prices usingLSTM model.

d. Model Architecture

The review focuses on Deep NeuralNetworks - Recurrent Neural Network. The review utilizes Long Short-Term Memory models from each of the aforementioned types of neural networks. Generalarchitecture of neural networks used.

Long Short-Term Memory (LSTM) Model – This modeluses a four hidden layer stacked stateful LSTM neural networkin which the input layer gets the input dataset consisting of thefeatures mentioned above. In each hidden layer, there are hcells which are completely connected to the input and outputlayers. Output layer consists of one cell, which had the outputfor the predicted price of the second minute from the currentinstance. The model was architected to be stateful to use themost important feature of LSTMs which is remembering theprevious states since in stock price prediction the previousprices play a significant role in

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predicting the future prices.Here a sliding window approach was utilized, where in a window of past 20 prices was considered. This approach made ustreat this problem as a time-series prediction problem, and asmentioned previously LSTMs have been conventionally verysuccessful for various time-series prediction problems.

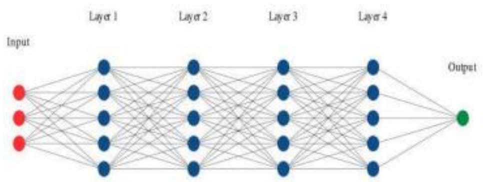

Figure 2. LSTM Layers

ReccurentNeuralNetworks(RNN) :

RNNsareanamazingandstrongsortsofNeuralSystems.InaRNN,thedatagoesthroughacircle/loop.WhenitsettlesonachoicE,itmullsoverthecurrentinfoandfurthermore what it hasgainedfrom the sources ofinfo it gotbeforehandor previously.ARecurrentNeuralNetworkfeedsitselfwithtwoinputs,thepresentinputandtherecentpast.ThisisimperativeandCrucialbecausethesuccession/sequenceofinformationcontainsurgentdataaboutwhat'scomingstraightawayandthat'sthereasonRNNcandothingsotheralgorithms can not.

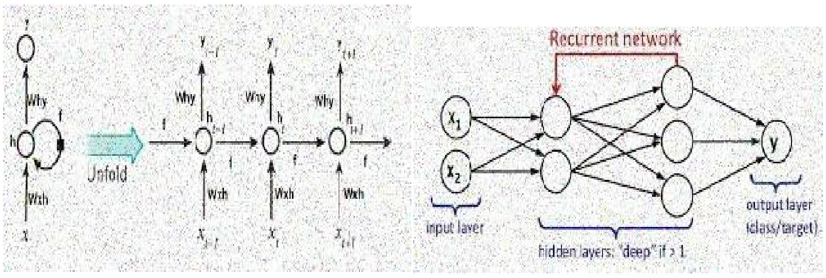

Figure 3. Neural and Recurrent Neural Network

IV. Results and Performance Analysis

For Checking Amazon Stock Prices

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Figure 4. Past two years prices for particular stock

The predictions shows in the below table 2 has the error of MAPE AND RMSE which shows that DNN_LSTM model is more accurate than the RNN model.

RMSE = math.sqrt(mean_squared_error(y_test, y_test_pred))
MAPE = np.mean(np.abs((y_test-y_test_pred)/y_test_pred))*100.

Predictions by the proposed model shows the high prices, open price, low price and close price in the table 3. which shows the accuracy of 90%. The figure 5, figure 6 , figure 7, figure 8 shows the actual and predicted prices for close , open , high and low where x -axis is the price in USD and y-axis is the time in minutes for next 7 days predictions.

Error	DNN_LSTM	RNN
RMSE	207.39625011831603	387.98531714439815
MAPE	5.647866406880419	10.593154965305416

Table 2. RMSE and MAPE error

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Next seven datys Prices	1	2	3	4	5	6	7
Open	2578.203	2625.809	2609.774	2545.546	2540.196	2602.665	2683.457
Close	2570.694	2574.751	2574.244	2522.672	2562.578	2626.764	2687.465
High	2600.432	2598.446	2582.546	2532.546	2573.292	2638.848	2675.694
Low	2582.365	2564.732	2548.946	2508.866	2544.476	2601.146	2672.244

Table 3. Stock predicted prices for next 7 days

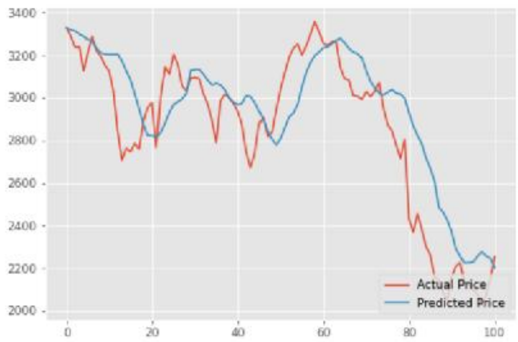

Figure 5. Close Price

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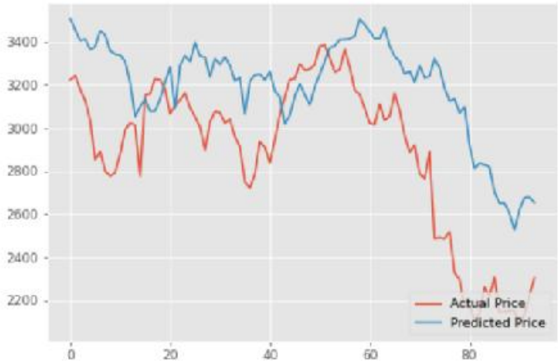

Figure 6. Open Prices

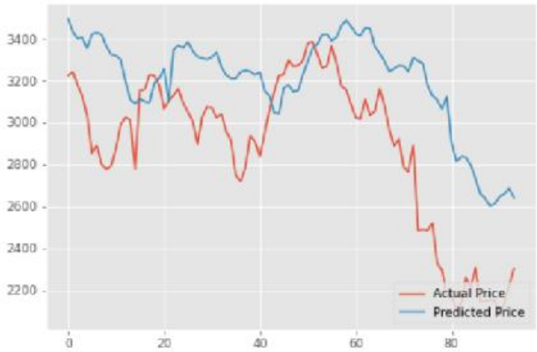

Figure 7. High Prices

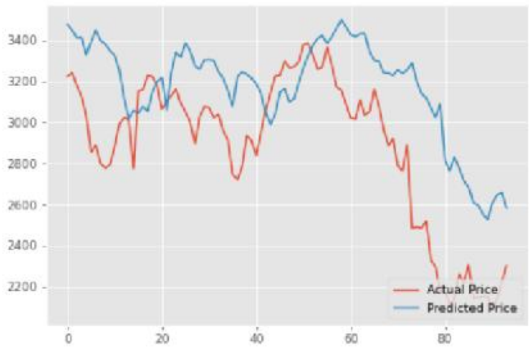

Figure 8. Low Prices

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V. Conclusion and Future Enhancements

The stock analysis itself is a cumbersome task to undertake. By using the comprehension of both algorithms, a sustainable prediction level has been achieved. Successfully scraping, then cleaning and then storing the data, our system is able to predict the future values of the stocks. The final system is a web based application, which is able to visualize the historic time series data and future prediction, along with news. The web based application in FLASK, with the implementation of database and visualization tools is able to show the interactive plots of the scores. Finally we were able to achieve our objectives through the build system. System can predict the value of company stock according to the data provided to the system to train it. We can analyze the current state of the current market. Simple interface and interactive charts of the system has made easy analysis of stock for the system users. Time series stat model DNN has been implemented & achieved high accuracy rate. Our system is able to predict all the company stock values taking the closing value only. Besides reaching our main objective to predict the value we are able to add different features to our system. We have managed to add the news features to the system where users are given access to view different stock news. Although we have reached our objectives but we are not fully able to get the accuracy completely. We are able to achieve accuracy upto 95% maximum and 90% minimum. We will be adding other feature in future to increase accuracy.

The proposed system is to be developed with inclusion of more companies in the future along with multiple news sources. The current system is build using the Auto regressive integrated model to increase the accuracy, different combination of DNN order were generated. By selecting best DNN order we are able to obtain accuracy up to 90% or higher. A system is never fully completed as we can enhance the system in future using different methods. Some of the future enhancement that can be done to the system are: 1. We can predict the stock value based on additional parameters such as opening values, turnover etc. 2. We can add different additional features like alerting the user about price rise/fall of different company's stock. 3. We can further integrate different algorithm to enhance the accuracy of the system

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