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Share Market Prediction using Twitter Sentiment Analysis

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Abstract **- We live in the digital era, where the volume of social media activity has reached previously unheard-of proportions in recent years. Twitter is one such prominent online social networking and micro-blogging site, which allows hundreds of millions of people to exchange brief messages in real time about events that deserve widespread notice, as well as to voice public opinion on such events. According to the findings of this study, there is a connection between Twitter sentiment and stock market movement. We are particularly interested in determining if and how effectively sentiment information collected from Twitter can be utilized to forecast future changes in stock prices. Market forecasting is a prominent and significant subject in financial and academic research, as well as in the financial industry. In order to do this job, time series analysis is the most frequent and basic technique that is utilized. The past three months' worth of tweets mentioning a certain businesses are gathered together. The outcome of this experiment demonstrates a statistically significant relationship between changes in daily stock price and changes in polarity of tweets calculated using sentiment analysis of tweets (polarity of tweets).**

Index Terms **- Sentiment Analysis, Twitter data, Share market prediction, Data analysis.**

1.INTRODUCTION

Data has been primarily utilized in the last 40 years to record and report company operations and scientific transactions, and it will also be used in the future 40 years to influence corporate choices and accelerate scientific discoveries. In recent years, the Web has become an open forum, where people may express their feelings and be heard. Numerous online social media platforms allow people to submit views such as social networking sites, wikis, blogs, Twitter, forums, and others. These articles offer comprehensive, useful knowledge about numerous points or occurrences that may be utilized for successful results in diverse applications. Using this online data by extracting important information from it is one of the big problems in data mining and knowledge discovery. These unstructured data offer important information to create new services for governments, companies, or people. Being able to anticipate future stock market movement is very investor's ambition. The two main methods are fundamental analysis and technical analysis in stock-market prediction. Researchers put a lot effort here, but it remains a tough issue. Coming from numerous sources and news Information is vast and tough to comprehend. There has been much study in recent decades in a number of areas, tackling this issue and proposed other methods. Recent development in machine learning area sparked numerous scholars and focused back to this field. In the last three decades, Artificial intelligence has evolved rapidly from multilayers to deep neural networks 1](DNNs) resembles neural convolution (CNN)[2] and long-term memory (LSTM). The finance Sector is undoubtedly one of the most popular where individuals see possibilities to use DNNs effectively. Bollenet al.[3] utilized twitter to forecast market movement; Chen et al.[4] used LSTM and basic Stock statistics includes Open, Close, High, Low(OCHL) stock-market forecast prices discovered Improvement of traditional techniques. Nelson, al.[5]LSTM experiments and stock technical indicators OCHL derived, exceeding traditional techniques with few exceptions. However, the findings showed new methods capable of attaining satisfactory precision. The stock market adapts new technology. To better investigate this issue, we created a dataset includes OCHL pricing, sentimental tweets and technical indicators and LSTM model experiments to forecast future stock price movement. The feeling is based on StockTwits' financial tweets. M ost popular financial and investing platforms. For hundreds of financial tweets a day, we use a different method to calculating collective feelings. SinceStockTwits began gathering feelings in 2017. Experiments are conducted to analyze the various Machine and Deep Learning algorithms and choose the effective algorithm for predicting the stocks. Also, to predict the costs price of the stock in the future days.

literature survey

Social networking platforms have become rapid and low-cost communication that allows users to quickly and easily obtain political information. During political elections, social media users share their feelings and views towards various parties and leaders. Initial studies typically showed positive findings on Twitter's forecasting ability related to election outcomes. Some studies found that candidate or party volume references alone indicated election outcomes [Gordon,(2013)].

There are numerous media where individuals may express themselves on the web. Blogs, wikis, forums, and social networks are examples of such media where users may submit information, thoughts, and get response from other users. They together offer a vast source of knowledge on various areas of life, but more importantly on diverse subjects, from politics and health to product evaluations and travel. The growing popularity of personal publishing services of many sorts indicates that opinion information will become a significant component of online textual data.

1.Social Media Analysis

The use of social media data has become more popular in the fields of information retrieval (IR) and text mining, owing to the large amount of real-time unstructured data available. Their emotions may be expressed via every tweet, comment, and blog post [Jain and Kumar, 2015a]. These unstructured data sets include valuable information that may be used to develop new services for governments, businesses, and individuals. The use of this unstructured data resulted in the development of a new field known as opinion mining and feeling analysis…

2.Social Media Analytics in Political Election

Today, every political campaign has a presence on social media, thanks to the efforts of academics from a variety of fields who are interested in extracting insights from this information. Facts and opinions are the two most common types of online writings found in social media data: facts and views. On the one hand, facts are regarded to be true, while opinions are thought to communicate subjective information about an object or problem on the other. Online social networking platforms like Twitter, for example, are one of the most fast and easiest ways to disseminate breaking news and political viewpoints. Election experts think that Obama's use of social media had a role in his victory in the 2008 United States presidential election [Matthew and Dutta, 2008]. The ability to communicate effectively in a unique way is critical in winning elections through microblogs such as Twitter [Kaplan and Haenlein, 2010]. The usage of gaming platforms such as Xbox gaming is also being utilised to forecast elections [Wanga et al., (2014)]. According to McComb and Shaw (1972), the question is whether mass media sources really accurately reflect political reality in its entirety. People's need for information and attention, according to Whinston and Huaxia (2010), is recognised and connected via the unique social media innovation; thus, its design should encourage such a link. It has been shown that obtaining political information on the internet is associated with political discussion and online civic messaging. This has been reported by Shah et al (2005). Xenos and Moy (2007) demonstrated that online information had direct effects on political knowledge and differential effects on politically-moderated involvement, as well as on both.

3.Social Media Analytics in Healthcare

Because the crisis has arisen as a result of epidemic activity that has caused tremendous harm to human life, it is absolutely critical that governments and public health organisations communicate to the public with accurate, timely, direct, and relevant messages through social media or other broadcasting means as soon as possible. It is critical to provide accurate information during health emergencies in order to mitigate the effects of pandemic disease. By detecting epidemics and strengthening public health information systems with the use of social media data, we may be able to mitigate the tremendous damage done to human life. Several authors, including Chew(2010), used social media data to detect disease outbreaks during the 2009 H1N1 pandemic, including Chew(2009), who used Twitter to identify illness outbreaks. It is based on a certain set of keywords. Additionally, different authors made use of a variety of additional keyword-searching techniques, such as internet search queries that were related to the flu [Signorini, 2009]. When utilized in the gathering of tweeter-related data, a technique based on specific search terms (flu, vaccine, tamiflu, h1n1) yields high accuracy when applied to the data. Content analysis and regression models were used to evaluate and monitor public concern and disease levels during the H1N1 pandemic in the United States, as reported by Hu et al. (2011) and Lampos and Cristianini (2010).

4.Social Media Analytics in Sports

Predicting success (winners and losers) in single-game and sports team competitions may be accomplished using a variety of methods. It is quite difficult to anticipate the outcome of these events when the teams and individuals are great competitors. There has only been a small amount of research on predicting outcomes using social media data. Wang (2013) reports that team fans and players use social media to express their feelings and points of view. Using data from the 2014 FIFA World Cup on Twitter, Yu and Wang (2015) were able to evaluate emotion users and create event-based tweet reactions. The outcomes of English Premier League games played during the 2013-2014 season have also been studied by several academics using sentiment analysis [Godin et al., (2014); Radosavljevic et al., (2014)]. Sinha et al., (2013) used n-grams from Twitter data sets to predict and compare National Football League (NFL) outcomes with other basic statistical methods in order to forecast and compare NFL results.

5.Sentiment Analysis

Jain and Kumar, 2016c] classed existing sentiment analytical work as a problem of text classification in a variety of different ways including document sentiment analysis, sentencing analysis, aspect-based feeling analysis, comparative sentiment analysis, and lexical feeling acquisition.

SYSTEM DESIGN

This section briefs about the methodology employed in implementation of the predication of stocks cost using historic data and social media opinions.

Predicting stock market deviation using ARIMA and LSTM algorithm works by collecting the data, processing it, and then displaying the outcome after prediction through table and graph format. It's split into three major components. These are Historic Data module, Module of Current Market Analysis and Module of Result and Prediction. The historical data module is further split into the data collecting and pre-processing module, the current market analysis comprises the sentiment analysis module and the data training module.

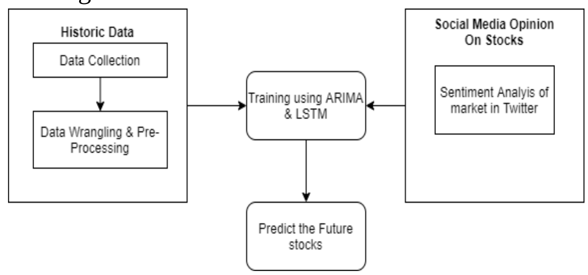

Figure 1: Block Diagram of the Predication System

Data Collection

The module collects real-time data using the system's "get symbol" function. Data is collected using the opening and closing valuation of the company [16]. It then displays a date-to-value graph on the x and y axes accordingly to illustrate the home screen outcomes. The instance of data collection is as shown in the below figure,

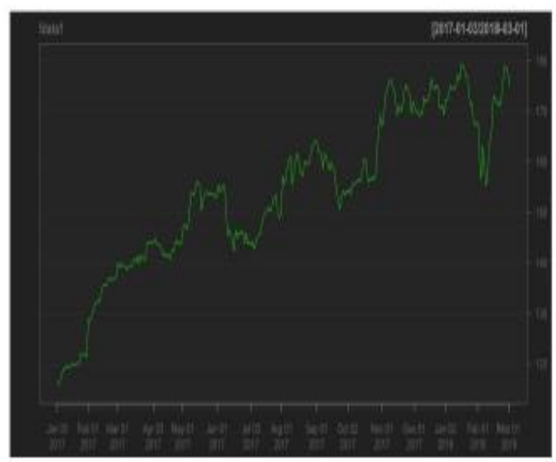

Figure 2: Data collection of the stock.

Data Pre-processing module:

Data Preprocessing module cleans any spurious values and accepts just the necessary parameters. The predictive factors in this method include date, volume, opening and closing value of business stocks on the market. The preprocessing program eliminates the remaining parameters and gives a clean set of system input data. The below figure shows the same,

	AAPL.Open	AAPL.Volume	AAPL.Adjusted
2017-01-03	115.80	28781900	113.8476
2017-01-04	115.85	21118100	113.7202
2017-01-05	115.92	22193600	114.2985
2017-01-06	116.78	31751900	115.5727
2017-01-09	117.95	33561900	116.6313
2017-01-10	118.77	24462100	116.7489
2017-01-11	118.74	27588600	117.3762
2017-01-12	118.90	27086200	116.8861
2017-01-13	119.11	26111900	116.6803
2017-01-17	118.34	34439800	117.6213

2017-01-18	120.00	23713000	117.6115
2017-01-19	119.40	25597300	117.4056
2017-01-20	120.45	32597900	117.6213
2017-01-23	120.00	22050200	117.6997
2017-01-24	119.55	23211000	117.5919
2017-01-25	120.42	32377600	119.4640
2017-01-26	121.67	26337600	119.5228
2017-01-27	122.14	20562900	119.5326
2017-01-30	120.93	30377500	119.2189
2017-01-31	121.15	49201000	118.9445
2017-02-01	127.03	111985000	126.1978
2017-02-02	127.98	33710400	125.9822
2017-02-03	128.31	24507300	126.5213
2017-02-06	129.13	26845900	127.7073
2017-02-07	130.54	38183800	128.9227
2017-02-08	131.35	23004100	129.4226
2017-02-09	131.65	28349900	130.3578
2017-02-10	132.46	20065500	130.0625
2017-02-13	133.08	23035400	131.2142
2017-02-14	133.47	33226200	132.9173
2017-02-15	135.52	35623100	133.3997

Figure 3: Pre and Post process of the Historic Data.

Data Training and Forecasting Module:

The training of the algorithm is achieved by two algorithms namely ARIMA and Long Short-Term Memory (LSTM).

ARIMA Algorithm:

This module takes into account both historical data and data on sentiment analysis. Most often, sentiment research comes into use only when market interest suddenly changes. It typically happens when the business policy changes, a software release or upgrade, poor publicity or negative media effect produced by influencers etc. This module is the most important module as it is used to forecast stock levels that the business may reach in the future (depending on user requirements). The prediction module analyzes the pattern shown by the supplied historical data and looks into the sentiment analysis module collecting information about the company's current standing with investors. It gathers business twitter data and classifies it into positive or negative classes, and if the class has more than tweet threshold values in it, the forecast changes. This is indicated by the displayed graph's direction shift. The ARIMA algorithm is presently set at 2 for auto regression, 2 for integration and 2 for moving parts, i.e. ARIMA.

An ARIMA model is referred to as ARIMA model letters (p, d, q), where p is the number of autoregressive components, d is the number of differences and q is the number of moving averages.

The process of self-repression. Autoregressive models imply Yt is a linear function of the previous values and is shown in the following equation.

$$Y_t = \alpha_t Y_{t-1} + \varepsilon_t$$

Each observation literally consists of two parts: a random component (random shock) and a linear blend of observations preceding it. The coefficient of self-regression is shown as number 1 in this equation.

Some processes may have a cumulative influence on the behavior of time series. For example, the stock situation is changing continuously as a consequence of consumption and supply, but the cumulative impact of all the instantaneous changes that take place in the period between inventories determines the average stock level. Although stock prices may vary by this average amount over time in reaction to major events, the long-term series level remains constant. The integrated process class includes a time series defined by the cumulative impact of an activity. Although the behavior of a series is unpredictable, variations from observation to observation may be very modest or even fluctuate around a constant value for a process observed at various times. The stationary of the series of differences for an integrated process is a key feature from a time series statistical analysis point of view. An example of the non-stationary series is integrated processes. A differentiation of order 1 implies that the difference is always the same between the two consecutive Y values. An integrated process is defined by the following equation.

$$Y_t = Y_{t-1} + \varepsilon_t$$

Where, εt is a white noise.

Moving Average Process:

A linear mix of the present disturbance with one or more previous disturbances is the current value of the moving averaging process, with the current disturbance being the most recently. The order of the shifting average indicates the number of preceding periods incorporated in the current value. The equation that defines a moving average is thus

$$Y_t = \varepsilon_t - \theta_t \varepsilon_{t-1}$$

1) Long Short-Term Memory (LSTM)

This study proposes a long-term, attention-based memory model for forecasting the direction of stock prices. The model is divided into four layers: the input layer, the hidden layer, the attention layer, and the output layer. The input layer cleans up the data to ensure that it meets the model input requirements. The line model network is connected to the hidden layer via the LSTM unit. The attention layer was given a numerical value by the vector. The results of computations are sent to the output layer. The gradient descent technique is used to address the problem of model training.

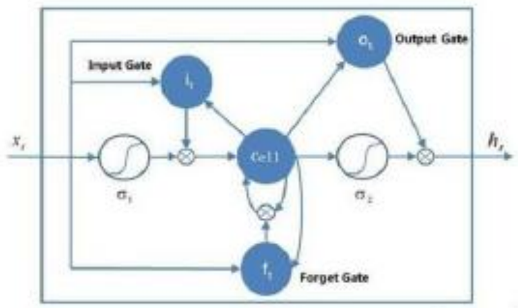

Figure 4: Logic for the LSTM.

The fundamental idea of LSTM is the cell state that is implemented via many gates. The cell state essentially acts as a highway, conveying important information across the sequence chain. It may be seen as a "network memory." In principle, the condition of a cell may include important information throughout the processing of a sequence. The novel LSTM-developed memory cell structure. A memory cell consists of four basic components: the input door, the output door and the neuron, which is a central linear unit with a fixed automatic connection in the centre. The memory cell decides what information should be kept and when to read, write and forget by regulating the three gates that periodically open and shut. The three gates must be used to calculate a value between 0 and 1.

Input Gate:

(1) Take the date, closing price, starting price, maximum price and minimum stock price as input data to create a time series;

(2) Divide input data into training set and test set by 70:30.

(3) Transform each input data component into interval [0,1] after standardization.

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

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

Forget Gate:

This gate decides whether information should be deleted or kept or not. The sigmoid function is used to transmit information between the prior hidden state and the current input. The values range from 0 to 1. The closer the number is near nil, and the closer it is to one, the closer it is to nil.

$$ft = \sigma\ (W_f.\ [\ h_{t-1}, x_t] + b_f)$$

Output Gate:

Once the model training is finished, the stock time series is then predicted. For instance, inventory data is input for N days to predict stock trends on N+1 days. In order to forecast the closing price for the fifth day of trade, the trained model uses transaction data from the first four trading days.

2) Twitter Sentiment Analysis

An emotion-based viewpoint or view is frequently referred to as a feeling. These passionate emotions from different user groupings are done in sentiment analysis when investigated and decided, their mindset towards the whole relevant extreme or enthusiastic response to a report, communication or occasion. Analysis of the sensitivity, allows the user to grasp the circumstances of what the review is about particular product or continuing issues, rather than comprehending the reviewer's deep ideas.

Twitter, one of many prominent social media platforms where individuals express their thoughts and ideas about a brand, item or help. Examining twitter feelings is extremely helpful in determining positively, negative, or neutral views of people. If people find significant or interesting things, then they'd like to offer their expertise on the topic. The subject may be an item, help, social message, or any other article.

Taking everything into consideration, with everybody's web-based beneficial experience so isolated and personalized, it may be tough to verify twitter evaluation and whether it's safe or bad from a single channel. Dismembering Twitter data and tweeting estimate may be much more simple than you would guess - go on to discover using our twitter supposition test model. Investigating internet networking realities like tweets helps people to think about a particular item or topic, making it easy to create choices about it. Furthermore, estimation inquiry makes a difference in people to alter their behavior regarding erroneous conviction on an item, administration or point. It causes people to choose the finest by analyzing comments or, on the other hand, tweets on a particular topic or object.

Client tweets from twitter are collected depending on the client's input as hash tags. The method to characterize tweets begins by first collecting tweets. Using Twitter API, you may collect twitter information. A library called RAuth is used to validate by entering keys. Purchaser Key, Consumer Secret, Access Token and Access Token Secret for twitter and handshake convention. After that, a statement is downloaded and the program produces PIN to receive tweets.

Live twitter information is now sorted according on estimates. That's feasible in 4 steps. In stage I tweets are collected by contributing to the kind of hash tags, and the number of tweets to be examined is restricted in the range between 5 and 1000. The tweets collected are those that were gushing live. Stage II prepares the collected tweets. Each tweet term is tokenized. Tokenization refers to the process of dividing a string arrangement into parts, e.g. phrases, words, watchwords, image and other components called tokens.

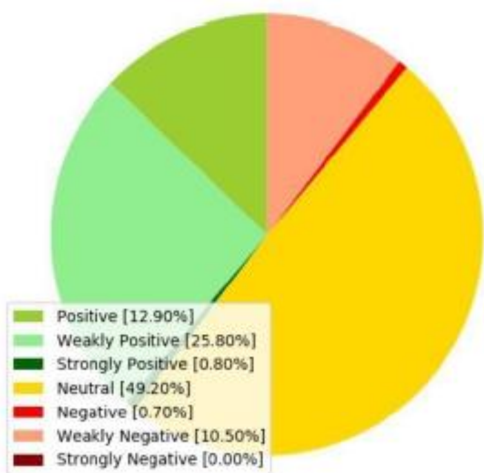

Figure 5: People reaction towards Reliance Stocks in Twitter.

Technical Analysis utilizing indicators

A technical analysis utilizing technical indicators is an art of analyzing past stock data such as price movements, volumes and market patterns. Thus, predicting future stock movements in the form of graphs and charts will assist investors anticipate what's more likely to happen to prices over a shorter period of time so they can make educated decisions. Technical analysis research consists mainly of a person selecting an optimum period or time to enter/invest in a specific asset and leave to produce maximum profits or minimum losses. Such choices rely on price functioning, signals provided by them, and market crucial turning moments. Technical analyzes are mostly types of technical indicators that assist investors detect such movements and patterns.

Technical indicators are mathematical formulae used to characteristics such as open, high, low, close to a particular stock obtained from different financial institutions or companies and then displayed as a graph. Different kinds of technical indicators are classified by what they are used for.

Four main technical indicator categories include

- Trend
- Volatility
- Momentum
- Volume

Trend: These technical indicators assist identify stock direction and strength. Usually the pricing plot is levelled and represented by a single line. Because of this procedure, the indicator lacks the sudden price shift termed trends. One of the main drawbacks is that such indicators lose money when the market is unstable. One of the key trend markers is: (1) moving average convergence divergence (MACD), the below figure shows the MACD analysis of the airtel company.

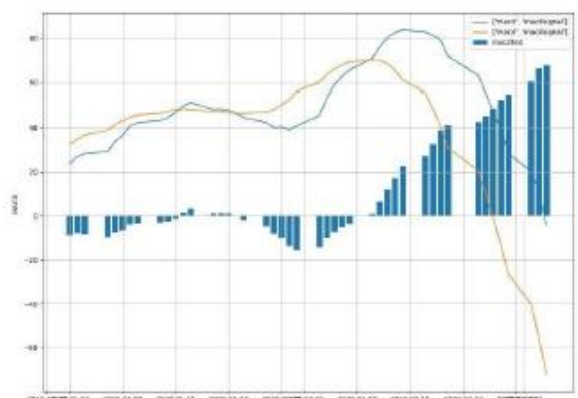

Figure 6: Analysis of Airtel.

Volatility Indicators — The analysts' volatility indicators assist them determine precise entry-exit points for each transaction. They are used to determine movement rate ignoring its orientation. One of the main indicators is Bollinger Bands.

If the Bollinger bonds are going down as shown in the below figure, its good to leave the trade.

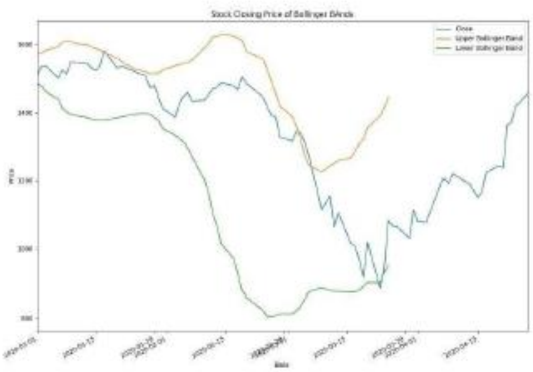

Figure 7: Down Fall of the Company Trades.

Momentum: - Momentum indicators assist identify price changes by comparing prices across many distinct periods of time. Comparing the current closing price with the previous closing price calculates it.

Volume: Volume is number of shares traded in a certain timeframe. A timeframe may vary from 1 to 1 Year. Volume plays an essential influence in determining a specific stock's direction or price. Volume-based technical indicators concentrate on volume-based calculations.

RESULT AND ANALYSIS

This section briefs about the results obtained in the phase of implementation of algorithm. The below figures shows the step by step execution.

The below figures shows the command to execute the program.

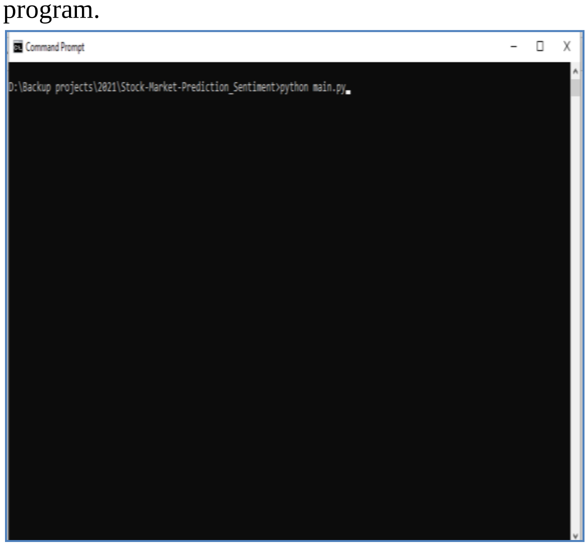

Figure 8: Execution Command

The below figures shows the command to run the server using runserver.

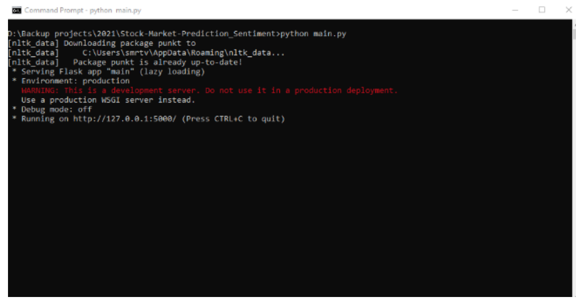

Figure 9 Turn the Local Server ON

The below figure shows that the program allows the user to enter the name of the stock in the local server page

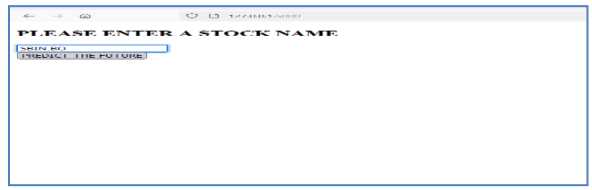

Figure 10: Program Allows the User to Enter the Name of the Stock to Predict the Cost of it.

The below figure shows the stock details which has been provided by the user in the earlier step.

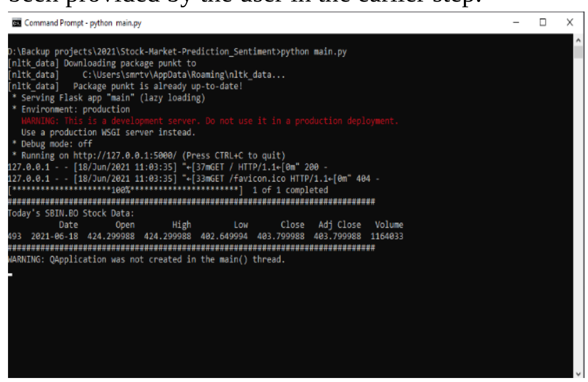

Figure 11: Stock details

The model training process is as shown in the below figure,

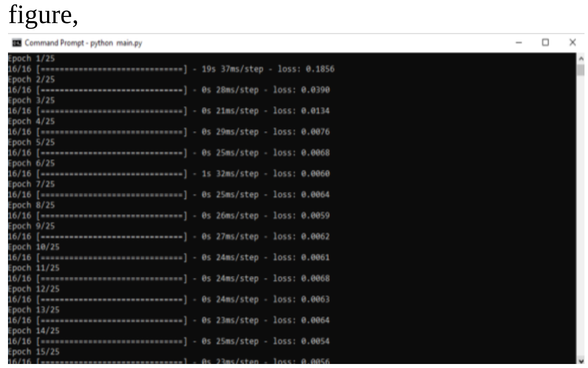

Figure 12: Model Training

The below figure shows the predication of the stocks using the ARIMA and LSTM algorithm,

Figure 13Predication of Stock Using ARIMA and LSTM.

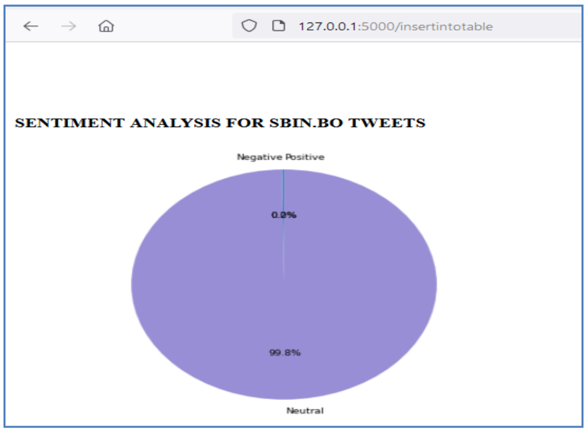

Figure 14: Social Media Analysis

The above figure shows the opinion of the people around the social media regarding the stocks.

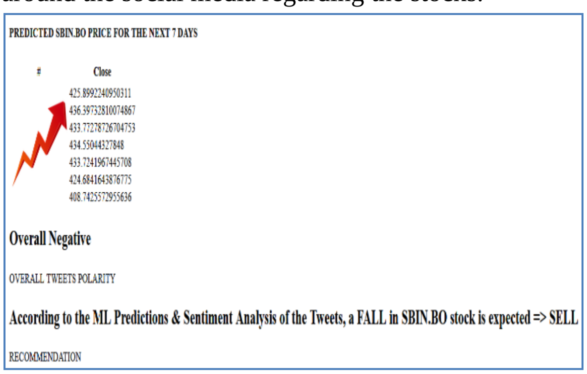

Figure 15: Predication of the stock for next seven days by employing Social Media Response.

The above figure shows the prediction of the stock for next seven days by the algorithm.

CONCLUSION

The popularity of stock-market trading is increasing fast, prompting academics to develop new predictive approaches utilizing new methodologies. The projection method not only assists academics, but also benefits investors and anybody with a stock market. To assist forecast stock indices, an accurate projection model is needed. Right now, numerous gage advancements have been used to assist financial experts, examiners or anybody interested in investing resources into the securities exchange by providing them excellent knowledge about the future circumstances of the securities exchange.

Future Work

The future scope gives the ways for the researchers to go along in the field some of the research areas are as follows,

1. Instead of having only two classes in sentiment analysis can extend to more to improve the accuracy.
2. To increase the sentiment analysis instead of taking data only from twitter can include blogs, online surveys, and facebook.
3. The automated messaging service for the investors during critical down and up of the market.

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