Catalyst Research Volume 23, Issue 2, July 2023 Pp. 58-72

ANALYZING TWEETS FOR PREDICTING THE SENTIMENTS OF INVESTORS IN THE STOCK MARKETS

Maheswari P
Department of Computer Applications, B.S Abdur Rahman Crescent Institute of Science and Technology, GST Road, Vandalur, Chennai, India, maheswari@crescent.education

Dr. A. Jaya
Department of Computer Applications, B.S Abdur Rahman Crescent Institute of Science and Technology, GST Road, Vandalur, Chennai, India, jaya@crescent.education

Abstract

An online social media has become a mirror for people's thoughts and opinions about news and events. In the stock market, sentiment drives almost all of its actions, and prediction is difficult because the stock market is dynamic and hard to predict. The purpose of this research work is to analyze the tweets of investors in the Adani Group after the Hindenburg report and predict how their sentiment might change. Investors who trade contrary to consensus are interested in the stock market's sentiment. The purpose of this research is to maximize investors' profits during periods of stock market volatility using Twitter sentiments. We analyze tweets from the Hindenburg report and predict investor sentiments. As a result, the result is strongly correlated with the forecast sentiment and the actual stock value.

Keywords- social media, twitter, Sentiment, Stock market, tweets, Hindenberg

1.0 Introduction

Globalization is undergoing a digital revolution. As a result of the Internet, the world of business has experienced a revolution. In 2023, India has the highest number of internet users in the top ten countries, with over 692 million users. People come together to share ideas and interests through social networking, which is an Internet-based community. It is called social media when it comes to sharing and collaboration. In terms of social media, there are Facebook, Classmates, Google+, Instagram, MySpace, Pinterest, Mix, Tumblr, Twitter, Yik Yak, and YouTube. There are 206 million daily active Twitter users who can provide you with breaking news, alerts, and tips that will help you make better trading decisions.

A tweet is a short message that people communicate on Twitter, an online news and social networking site. The purpose of tweeting is to send short messages to people who follow you on Twitter. The term microblogging can also be used to describe Twitter. In microblogs, tweets can be no longer than 280 characters. As a result of this size restriction, Twitter has become one of the most popular social networking tools. The content on Twitter is a rich source of information and useful news. Tweets are used to forecast investor sentiment in the stock market.

Shares of publicly-held companies are traded, sold, and issued on the stock market. The general public needs to know about the organization's assets and income because they will need it to survive. As part of its fundraising efforts, an organization may either raise funds from individuals or issue stocks in order to raise cash.

Section 1explores the impact of social media for digital revolution. Section 2 describes the impact of stock price for investor’s perspective. The section 3 discusses an overview of related work aboutstock prediction using Twitter. Thesection4 proposes a system for analyzing and predicting stock sentiment based on tweets. A discussion of the implementation and implementation results is provided in section 5. Section 6 presents the conclusion and future enhancements.

2.0 Impact of Stock prices

It is difficult to predict whether a stock price will rise or fall due to the multitude of variables that can influence it. Buyers and sellers of stocks were affected by the fluctuation of stock prices.

- Indicators of earnings and expectations
- Demand and Supply
- Indicators related to the economy
- Conditions in the industry
- Catching the big fish
- News
- Sentiment of the market

In a sentiment analysis, the speaker or writer describes their feelings toward a particular topic or the overall polarity of the document. Users of the website can track brands, products, people, etc., and determine whether they are perceived positively, negatively, or neutrally by the web community.In addition to being closed, measurable, and almost entirely sentiment driven, the stock market is an excellent example.

With the advent of social media, all opinions and thoughts regarding any event or matter of news can be reflected on it.Regardless of whether a specific organization is perceived positively or negatively, its stock prices may be affected gradually over time. By understanding Market Sentiment, investors can make better investment decisions.

A market sentiment describes investors' attitude toward a particular security or market. In the case of financial markets, it's the mood or tone of the market, as revealed by the prices and activity of the securities traded. Indicators such as "market sentiment" or "investor sentiment" are not always determined by fundamentals.

Traders and technical analysts use market sentiment to gauge short-term price movements that are often driven by investor attitudes towards a security. They use technical indicators to gauge and profit from these movements. Investors who are contrarians seek to trade the opposite direction of market consensus should be aware of market sentiment. Suppose each investor is purchasing, while a contrarian is selling.

Hindenburg in a report published on January 24th 2023, outlined "Adani Group: How the World's Third Richest Man Is Pulling the Largest Con in Corporate History". Hindenburg Research is an investment management company with decades of experience. Besides forensic financial research, They also conduct corporate investigations. They specialize in credit, equity, and derivatives analysis. Hindenburg's report reveals that Adani Group's chairman has added more than $100 billion in three years, largely through stock price increases in the group's listed companies.

2.1 Impact of Hindenburg report

After the company's follow-on public offering (FPO) of $12,000 crore was approved on 17th January 2023, shares of the 10 listed entities of the Adani Group plunged on 1st February 2023. Adani Enterprises' stock has dropped over 25% since Hindenburg Research released its report.

A 20,000 crore FPO from Adani Enterprises was fully subscribed with support from HNIs and institutional investors. The offer was not well received by retail investors and even company employees despite its attractiveness. As Adani stocks decline, euphoria over the budget fades away in the capital markets. Adani Ports and SEZ, Adani Green Energy, and Adani Electricity Mumbai sold bonds with a zero-lending value to Credit Suisse, the global brokerage firm.

Within just five trading sessions after Hindenburg Research published its exhaustive report charging Gujarat-based Adani Group with accounting fraud and stock manipulation, shares of 10 listed companies owned by the company plummeted. With a combined market value of approximately 7.4 lakh crore, the combined market capitalization of the group has fallen by more than 35% in just five trading sessions.

This research work seeks to analyze in detail the tweets regarding the Hindenburg report concerning the Adani Group of Companies such as ACC, Adani Enterprises, Adani Green Energy, Adani Ports & SEZ, Adani Power, Adani Total Gas, Adani Transmission, Adani Wilmar, and Ambuja Cement to predict the sentiment of the investors.

3.0. Related Works

Twitter users' Covid-19 data can be extracted in three steps. According to Yuxing Qi et.al [1], The difference between predicted and real results can be compared using an annotated dataset. It is possible to analyze changes in attitudes and perceptions over time through Covid-19 studies based on time series.

In their study, Yalanati et.al. [2] demonstrated that combining LSTMs and BERTs can provide an effective method for predicting stock prices.Muhammad Khurram Iqbal et.al.[3] found that the ensemble voting classifier was 85.33% accurate and the ensemble stacking classifier was 87.55% accurate when compared to other classification algorithms.

A. Jagini et al.[4] As part of their study, VADER is used to calculate the sentiments of each tweet about bitcoin as well as the profession and follower count of verified users who tweet about bitcoin. Using historical bitcoin price data combined with tweet related data, a model is trained and tested. The sentiment of tweets is correlated with changes in the bitcoin price, according to the study. In the study by Moritz Wilkschet al.[5], they demonstrate that their model provides comparable performance to BERT-based models for large languages.Because the model is simple, it can be trained at a fraction of the costs and inferred at a fraction of the time. To facilitate the use of the artifact by future researchers and practitioners, it is published as a Python library.

XiangLing Fu et al. [6] analyze the P2P platform trading data. A correlation has been found between investor sentiment and the P2P platform's exchanging volume. Using TextCNN model, they classified investor remarks by sentiment and obtained the time series of sentiment changes. This model increases Pearson coefficients by 13.26% for predicted and actual values, decreases mean squared errors by 27.62 percent, and increases Rsquared by 28.48 percent in comparison with baseline regression [6].

Rather than categorizing texts as positive or negative, Bharat Gaind et al. [7] analyze them based on six basic emotional categories. According to Salvatore Carta et al. [8], they fine-gauged ARIMA's parameters and examined various mixes of exogenous facets and found that Google Trends data drastically improved forecasts. According to Rupali Borole et al. [9], their algorithm took into account the views of viewers on stock shares. The stock market is one of those fields where the opinions of users are crucial. Traders who want to enter the market have been greatly influenced by the views of the experts. Methods that are dependent on unsupervised and supervised learning help to locate the results more effectively.

In a study conducted by Franco Valencia et al. [10], machine learning and sentimental analysis have been found to be capable of predicting cryptocurrency market price movements in the same way that Bitcoin price predictions had previously been accomplished.In addition, three prediction models based on Twitter data, market data, or both were evaluated and compared for Bitcoin, Ethereum, Ripple and Litecoin.

A real-time monitoring system for social media and digital press is Talaia, according to San Vicente et al.[11].Talaia uses natural language processing to extract relevant information and analyze it. In order to minimize the domain adaptation process, both from a data collection and annotation perspective, experiments are being performed on a sentiment analysis model for a new domain.

A large amount of research is still needed to improve the management of live streaming data, according to Abhijit Bandyopadhyay [12]. In future work, MySQL concurrency issues can be analyzed effectively with the goal of achieving optimality and minimizing errors. A sentiment analysis of public mood can eventually be used to predict movements in stock prices using data derived from twitter feeds, according to Sushree Das et al. [13] An incremental active learning approach was used to adapt the methodology to a stream-based setting.

The findings of Texas Mankaret al.[14] have demonstrated that Support Vector Machines are the most effective and viable model for predicting stock price movements based on sentiments expressed in tweets. When compared to other methods of measuring public mood, using Machine Learning techniques can be more economical than conducting a bottom survey.

The accuracy of the SVM models constructed by Rakhi Batra and Sher Muhammad Daudpota [15] in their training and test groups was recorded at 75.22% and 76.68%,

Catalyst Research Volume 23, Issue 2, July 2023 Pp. 58-72

respectively.As demonstrated by YefengRuan et al. [16] using their trust arrangement power based method to weight tweets, the sentiment valence of Twitter tweets reflected irregular stock returns better than treating all the creators equally significant or weighting them based on their number of followers.

Sahar Sohangir et al. [17] examined StockTwits data to see if they could improve sentiment analysis accuracy by using VADER, SentiWordNet, and TextBlob. Log regression, linear SVM, and Naive Bayes classification were compared with lexicon-based models and machine learning models. Furthermore, VADER outperforms AI in the removal of assessments from budgetary web-based activities, similarly to StockTwits [17].

To clarify the path for future improvement, Yan Chen et al. [18] developed three main issues framework for large challenges, including media content, media representations, and analysis models.

The model was developed by Delia Iraz Hernández Farrari et al. [19] They examined the ways in which full of feeling highlights are utilized based on the variety of lexical assets for English that reflect various aspects of effect. It has been demonstrated through analyses of various corpora that full-of-feeling data helps distinguish between unexpected and non-amusing tweets.

In a study performed by Hana Alostad et al. [20], they predicted the hourly stock price direction by analyzing news articles' content that mention a stock symbol. The LogisticR classifier was used with keyword features and sentiment features extracted from documents. In comparison with a framework using all news indiscriminately, breaking news-based forecasting provides a factually huge boost in forecast accuracy.

The paper by Apoorv Agarwal et al. [21] investigates the use of tree pieces to reduce monotonous element construction. The new includes (associated with recently proposed highlights) and tree parts outperform the cutting-edge benchmark in roughly the same way.

Based on the literature survey, there is a need for analyzing the sentiments of the tweet messages for predicting the stock market price for short term period. The next discusses the system for analyzing the sentiments.

4.0 Proposed Sentiment Prediction Framework

Inorder to analyze and predict the investors stock values for a short-term period, a SPF framework is proposed. There are four phases inthe SPFsentiment prediction system such as Data source, preprocessing, prediction and forecastwhich is depict in figure 4.2.

In Data source module, data is acquired from the from Kaggle datasets that are related to Hindenburg report on Adani Group of Companies on 24th January 2023. Twitter data is collected between 31st January and 7th February 2023 which consists of 1000 tweets.Figure 4.1 depicts The dataset of tweets related to Hindenburg report.

0	2023-02-0	1.62E+18	@hegade_u @JhaSanjay Let this Jha2 read carefully	0	0
1	2023-02-0	1.62E+18	@CursedSe7en @Memeghnad Yes and like RG bashe	0	0
2	2023-02-0	1.62E+18	@_pallavighosh ji So @RahulGandhi has spoken on H	0	0
3	2023-02-0	1.62E+18	With so much venom being spewed by Congress dyna	0	0
4	2023-02-0	1.62E+18	Hindenberg is banned by SEC from participating in US	2	0
5	2023-02-0	1.62E+18	RaGa is not attacking Adani. He's attacking the bigge	0	0
6	2023-02-0	1.62E+18	Adani group faces the severe losses of $100 BILLION	0	0
7	2023-02-0	1.62E+18	A very intersting point raised by @RahulGandhi. The	113	46
8	2023-02-0	1.62E+18	Hindenberg report, climate change & Gujarat	1	0
9	2023-02-0	1.62E+18	India's Rs 20 lakh crore Covid relief package was	0	0
10	2023-02-0	1.62E+18	Markets in India and abroad accepted my vision of In	0	0
11	2023-02-0	1.62E+18	@sumanthraman What's new in this. This is what Hin	0	0
12	2023-02-0	1.62E+18	@wowindian @SadhguruJV He lost 1 follower today	0	0
13	2023-02-0	1.62E+18	A small reminder to Mr #GautamAdani	0	0
14	2023-02-0	1.62E+18	@SpiritOfCongres Arey lath core. U got caught. Sadg	0	0
15	2023-02-0	1.62E+18	7/ Companies must meet specific eligibility and	4	4
16	2023-02-0	1.62E+18	2/ A lot has happened with the #Adani Group after	3	3
17	2023-02-0	1.62E+18	@rishibagree Aare chintu sahab, nobody is asking to	5	0
18	2023-02-0	1.62E+18	@mchellap As long as the report is based on hard co	0	0
19	2023-02-0	1.62E+18	@AJEnglish IF PM MODY IS NOT GUILTY OF CARNAG	0	0
20	2023-02-0	1.62E+18	@_onlyAjinkya @MahuaMoitra @CVCIndia	3	0
21	2023-02-0	1.62E+18	@virendersehwag Aap jo karte hai cricket wahi kro..!	0	0
22	2023-02-0	1.62E+18	@rishibagree But it was not due to Hindenberg repor	0	0

Figure 4.1 Tweets dataset related to Hindenburg Report

The preprocessing phase, Removal of Hashtags, URL, duplicate tweets, special characters, numbers, punctuation marks, removal of emojis, stop words and twitter mentions in the data sets. The Preprocessing of tweets is done using tokenization and POS tagging. In this phase, Data from the training dataset makes up 80% of the original data, and data from the testing dataset makes up 20%.

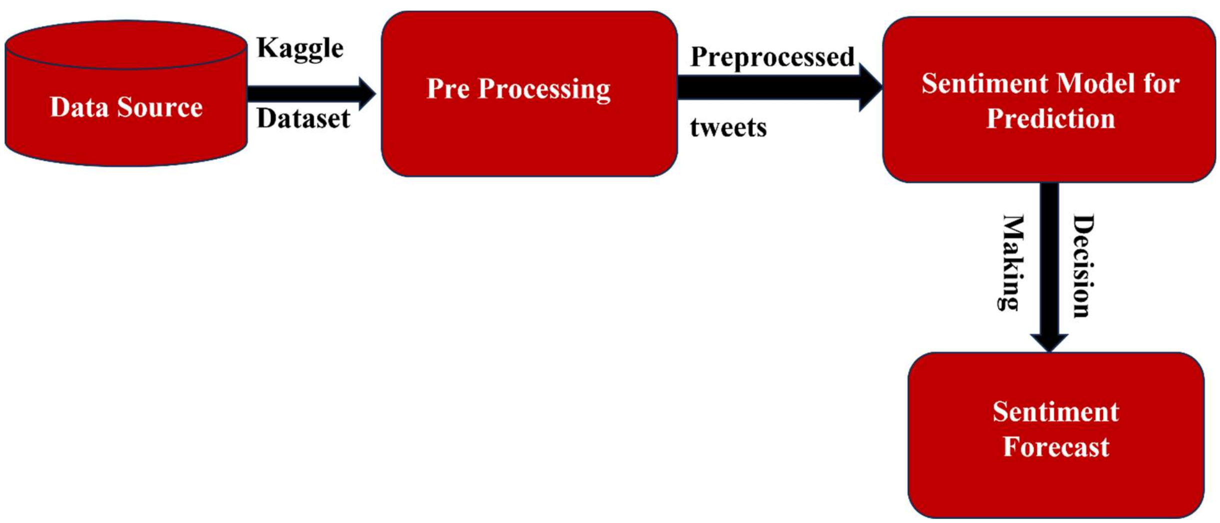

Figure 4.2 Conceptual diagram for SPF_framework

In the prediction phase, Sentiment model for prediction VADER(Model – 1) and RoBERTa(Model- 2) are used to predict investor sentiment.Figure 4.2 depicts the VADER and ROBERTA systems are compared in the third phase of the proposed stock sentiment system.

Catalyst Research Volume 23, Issue 2, July 2023 Pp. 58-72

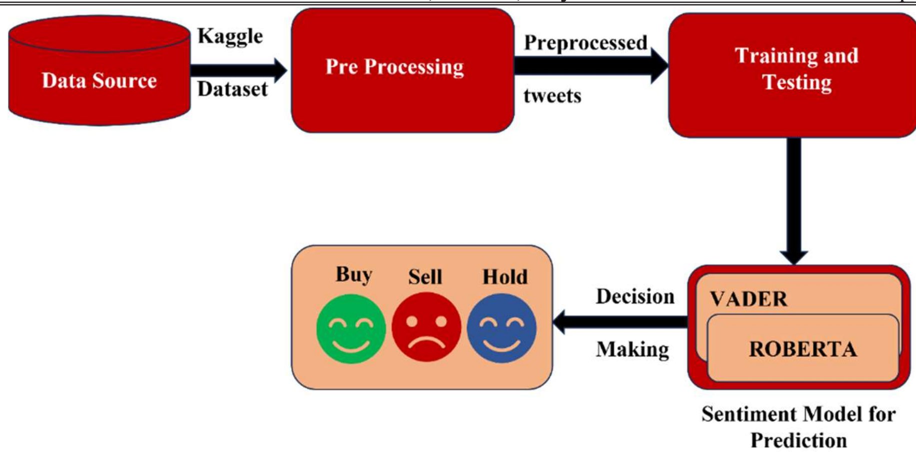

Figure 4.3 Illustration of Sentiment Prediction Framework

A VADER model for sentiment analysis uses the Valence Aware Dictionary and Sentiment Reasoner to provide simple rule-based analysis. The algorithm relies on unsupervised learning.

4.1 Algorithm to forecast the twitter sentiments of the investors using VADER – Model 1

The algorithm predicts the investors sentiment from their tweets.

Input Data: tweets from the twitter of the particular stock companies.

Step 1: import all the necessary libraries.

Step 2: sentiment analyzer object is created.

Step3: preprocessing the tweets

Step 4: calculating the polarity scores.

Step 5: predicting the sentiments based on polarity scores.

Output Data: Sentiment of the investors of particular stock companies are predicted.

	id	neg	neu	pos	compound	Unnamed: 0	date	Tweets	likes	retweets
0	1622909048017375232	0.055	0.800	0.145	0.3818	0	2023-02-07 10:44:03+00:00	@hegade_u @JhaSanjay Let this Jha2 read carefu...	0	0
1	1622905625163481089	0.059	0.779	0.162	0.5106	1	2023-02-07 10:30:27+00:00	@CursedSe7en @Memeghnad Yes and like RG bashed...	0	0
2	1622902969892220929	0.000	0.870	0.130	0.2732	2	2023-02-07 10:19:54+00:00	@_pallavighosh ji So @RahulGandhi has spoken o...	0	0
3	1622901179343843328	0.044	0.901	0.055	0.1280	3	2023-02-07 10:12:47+00:00	With so much venom being spewed by Congress dy...	0	0
4	1622898358758293510	0.125	0.875	0.000	-0.4588	4	2023-02-07 10:01:35+00:00	Hindenberg is banned by SEC from participating...	2	0

Figure 4.4 Calculation of positive, negative neutral and compound score of VADER Model-1.

This algorithm predicts the sentiments of the particular stocks. In model-1, The Preprocessing of tweets is done using tokenization and POS tagging. Sentiment analyzer object is created. Polarity scores are calculated. Figure 4.4 depictsthe calculation of positive, negative, neutral and compound score of Vader Model – 1.The output is calculated in the form of dictionary containing positive, negative neutral and compound scoresThe compound score tells us the intensity and polarity of the tweets.

Catalyst Research Volume 23, Issue 2, July 2023 Pp. 58-72

4.2 Algorithm to forecast the sentiments of the investors from the twitter using RoBERTa (Model -2)

The algorithm describes predicting the sentiments of the investors from twitter.

Input Data: tweets from the twitter of the particular stock companies.

Step 1: start

Step 2: import all the necessary libraries

Step 3: Data is loaded.

Step 3: Preprocessing the tweets using Distil BERT to kenizer.

Step 4: Training and testing datasets are divided using the map method.

Step 5:The model is trained by using the train() method.

Step 6: Compute the evaluation metrics.

Step 7: Analyzing new data with the model using pipeline class.

Step 8: Predicting the twitter sentiment Analysis.

Output Data: Sentiment of the investors of particular stock companies are predicted.

This algorithm predicts the tweets sentiment, Distil BERT to kenizer is used to preprocess the tweets. Using train method, the model is trained and evaluation metrics are computed. Using pipeline class analyzing new data.

A single application is capable of handling vocabulary, abbreviations, capitalization, repeated punctuation, and emotions efficiently. RoBERTa is abbreviated as Robustly Optimized BERT Pre-training the model was developed by Facebook AI specially for sentiment analysis.

This is reimplementation of BERT with a setup for RoBERTa pretrained models with modifications in key hyperparameters. It is a self-supervision fashion on large corpus which is a pretrained transformer model. In addition, it is unnecessary to define which token belongs to which segment, since token_type_ids are used. It is easy to divide the segments.

In the Sentiment Forecast phase,in figure 4.3depicts that decision making is based on the result if it is positive then the investors can buy the stocks else if it is negative the investor can sell and if it is neutral, then the investor can hold the stocks.

5.0 Implementation and discussion of the results

The SPF proposed stock sentiment prediction systems utilize VADER and RoBERTa method. This research works with tweets on Hindenburg report. Figure 5.1 depicts the compound score of Model – 1.

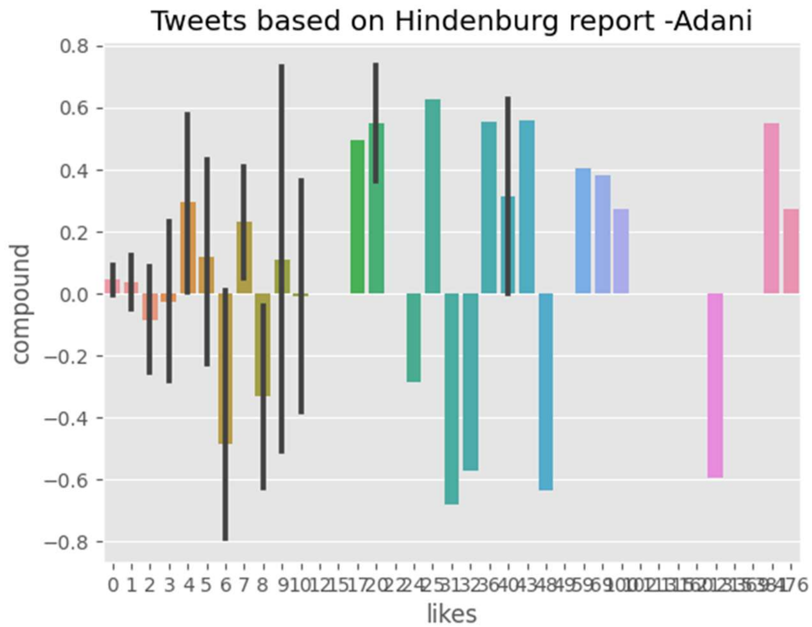

Figure 5.1 Compound score of VADER (Model -1).

According to this model -1, The sentiments of neutral has more score than negative and positive sentiments. Based on the figure 5.2depicts the positive, negative and neutral sentiments of Model -2 respectively.

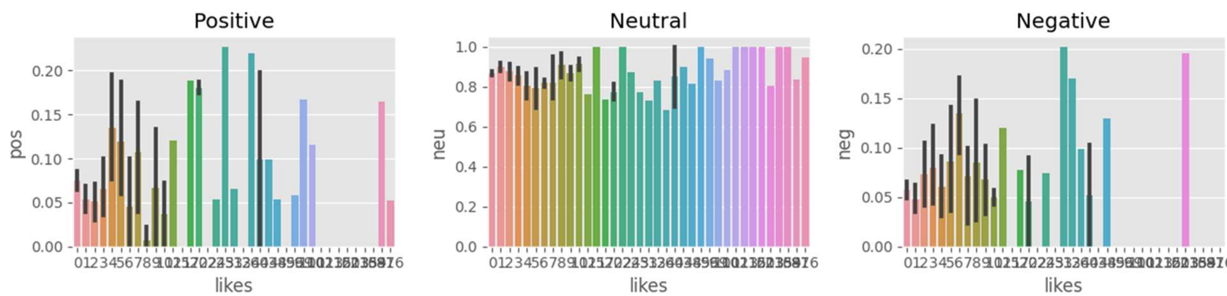

Figure 5.2 Prediction using RoBERTa (Model – 2)

Roberta has performed well than VADER.Roberta is a self-supervised learning whereas VADER is an unsupervised Learning. According to the twitter sentiments Roberta has more accuracy than VADER

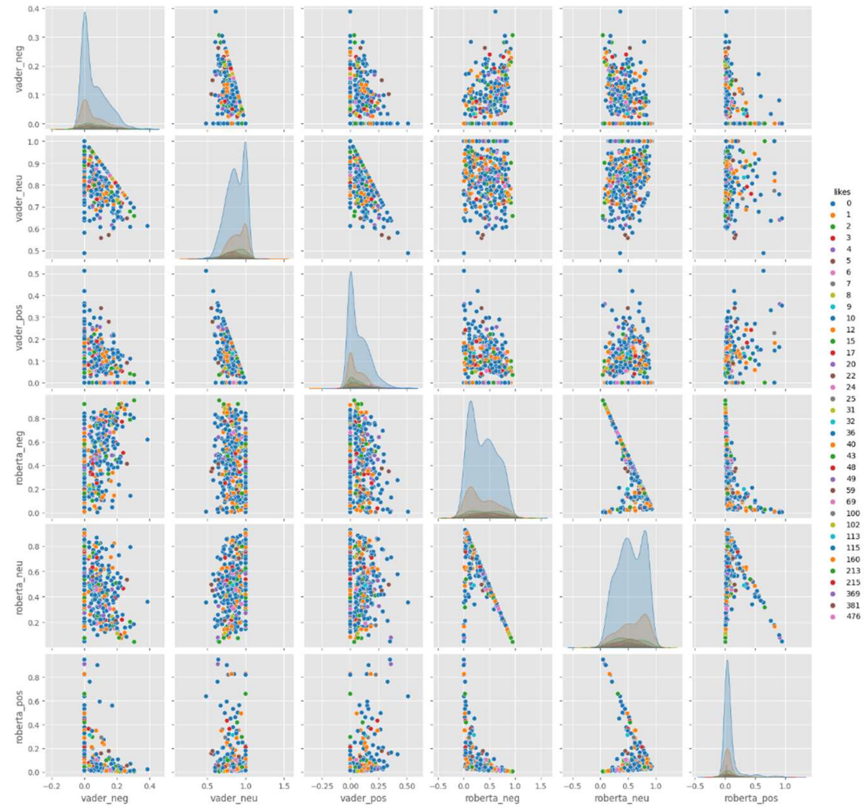

Figure 5.3 Comparison of VADER and RoBERTa using twitter

Accuracy of VADER Model -1:

{'neg': 0.169, 'neu': 0.831, 'pos': 0.0, 'compound': -0.8185}

Figure 5.4: Accuracy of Model -1

Accuracy of RoBERTa Model -2:

{'roberta_neg': 0.80724126, 'roberta_neu': 0.18566298, 'roberta_pos': 0.0070957537}

Figure 5.5 Accuracy of Model -2

Table 5.1 depicts the Accuracy of Model – 1 and Model- 2.

VADER (Model -1)		**RoBERTa (Model -2)**	
Positive	0	Positive	0
Negative	16.9	Negative	80.7
Neutral	83.1	Neutral	18.5

The figures 5.3 and table 5.1 depicts, the comparison of Model -1 and 2. Model-2 has greater accuracy score than Model- 1.

The proposed SPF stock prediction systems has proved that the accuracy of RoBERTa (Model -2) has more accurate than VADER(Model-1) which depicts on the table 5.1.According to the table 5.1, both models has predicted zero in positive sentiments that is no bull market is predicted. In Model-1 negative sentiments is low compared to Model-2, Negative sentiments is

16.9 in Model-1 whereas in Model-2 it is 80.7(negative). Therefore model-2 has more negative sentiments than model -1. In neutral sentiments model -1 has 83.1 and model-2 has 18.5. by comparing the both models Roberta Model -2 has higher accuracy than Model-1.

According to the Hindenburg report twitter sentiments of investors was negative. Within just five trading sessions after Hindenburg Research published its exhaustive report charging Gujarat-based Adani Group with accounting fraud and stock manipulation, shares of 10 listed companies owned by the company plummeted. With a combined market value of approximately 7.4 lakh crore, the combined market capitalization of the group has fallen by more than 35% in just five trading sessions.

6.0 Conclusion and Future Enhancement

As social media plays a significant role in stock market trends, an amazing tool for staying connected with the people and by using these internet-based platforms for communication, users can share information and web content.In stock market, Investors take information from a host of online sources to make their decisions. In this research work, we have compared the VADER and ROBERTa model for sentiment analysis using twitter our finding suggest that investors sentiment was negative. As per the result obtained on dataset, the accuracy Roberta is more compared to VADER. Researchers need to improve sentiment analysis' performance with Reinforcement Learning in order to predict the investors' sentiment.

7. References

[1] Qi, Y., Shabrina, Z, Sentiment analysis using Twitter data: a comparative application of lexicon- and machine-learning-based approach. Soc. Netw. Anal. Min. 13, 31 (2023). https://doi.org/10.1007/s13278-023-01030-x

[2] Yalanati Ayyappa; B. Vinay Kumar; Sudhabatthula Padma Priya; Siddiboena Akhila; Tamma Priya Vardhan Reddy; Shaik Mohammad Goush "Forecasting Equity Prices using LSTM and BERT with Sentiment Analysis", Published in: 2023 International Conference on Inventive Computation Technologies (ICICT) IEEE, DOI: 10.1109/ICICT57646.2023.10134443.

[3] Muhammad Khurram Iqbal, Kamran Abid, M fuzail, Salah u din Ayubi, & Naeem Aslam. (2023). Omicron Tweet Sentiment Analysis Using Ensemble Learning. Journal of Computing & Biomedical Informatics, 4(02), 160–171. Retrieved from https://jcbi.org/index.php/Main/article/view/145

[4] A. Jagini, K. Mahajan, N. Aluvathingal, V. Mohan and P. TR, "Twitter Sentiment Analysis for Bitcoin Price Prediction," 2023 3rd International Conference on Smart Data Intelligence (ICSMDI), Trichy, India, 2023, pp. 32-37, doi: 10.1109/ICSMDI57622.2023.00015.

[5] Moritz Wilksch and Olga Abramova, "PyFin-sentiment: Towards a machine-learning-based model for deriving sentiment from financial tweets", International Journal of Information Management Data Insights, Volume 3, Issue 1, 2023, 100171, ISSN 2667-0968, https://doi.org/10.1016/j.jjimei.2023.100171.

[6] Xiang Ling Fu, Shuai zhang, Jinpeng Chen, Tianxiong Ouyang and Ji ulu, "A Sentiment –aware trading volume Prediction Model for P2P Market using LSTM", Published in IEEE Access 2019 DOI:10.1109/access.2019.2923637.

[7] Bharat Gaind, Varun Syal and Sneha Padgalwar, "Emotion Detection and Analysis on Social Media", Published in the Global Journal of Engineering Science and Researches (ISSN 2348 - 8034, Pg. 78-89) in arXiv:1901.08458v2 [cs.SI] 12 Jun 2019.

[8] Salvatore Carta, Andrea Medda, Alessio Pili, Diego Reforgiato Recupero and Roberto Saia, "Forecasting E-Commerce Products Prices by Combining an Autoregressive Integrated Moving Average (ARIMA) Model and Google Trends Data "Published in Future Internet 2019, 11, 5; doi:10.3390/fi11010005.

[9] Rupali Borole, Sonali Govilkar, Dipali Duble and Manisha Sonawane, "Stock prediction marketing using machine learning", International Journal of Advance Research, Ideas and Innovations in Technology, ISSN: 2454-132X, Impact factor: 4.295, (Volume 5, Issue 1)2019.

[10] Franco Valencia, Alfonso Gómez-Espinosa and Benjamín Valdés-Aguirre, "Price Movement Prediction of Cryptocurrencies Using Sentiment Analysis and Machine Learning", Published in Entropy 2019.

[11] Iñaki San Vicente, Xabier Saralegia and Rodrigo Agerrib, "Real Time Monitoring of Social Media and Digital Press", Preprint submitted to Engineering Applications of Artificial Intelligence January 16, 2019 http://arxiv.org/abs/1810.00647v2.

[12] Abhijit Bandyopadhyay, "Extraction and Analytics from Twitter Social Media with Pragmatic Evaluation of MySQL Database", International Journal of Computer Trends and Technology (IJCTT) – Volume 57 Issue 2- March 2018.

[13]Sushree Das, Ranjan Kumar Behera, Mukesh kumar, Santanu Kumar Rath, "Real time Sentiment Analysis of Twitter Streaming data for Stock Prediction", International Conference on Computational Intelligence and Data Science (ICCIDS 2018) Elsevier Procedia Computer Science 132(2018)956-964.

[14]Tejas Mankar, Tushar Hotchandani, Manish Madhwani, Akshay Chidrawar, Lifna C.S, "Stock market Prediction based on social sentiments using Machine learning", Published in International Conference on Smart City and Emerging Technology(ICSCET) IEEE 2018.

[15] Rakhi Batra and Sher Muhammad Daudpota, "Integrating Stock Twits with Sentiment Analysis for better Prediction of Stock Price Movement", 2018 International Conference on Computing, Mathematics and Engineering Technologies – iCoMET 2018.

[16] Yefeng Ruan, Arjan Durresiand Lina Alfantoukh, "Using Twitter trust network for stock market analysis", Published in Knowledge-Based Systems Volume 145, 1 April 2018, Pages 207-218.

[17] Sahar Sohangir, Nicholas Petty and Dingding Wang, "Financial Sentiment Lexicon Analysis", 12th IEEE International Conference on Semantic Computing, 2018.

[18] Yan chen,Jun wang, Yuanzhu Chen, Hsinchun Chen," WEb Media and Stock Markets: A Survey and Future Directions from a Big Data Perspective", IEEE Transactions on Knowledge and Data Engineering 2017.

[19] Delia Irazú Hernández Farías, Viviana Patti and Paolo Rosso, "Irony Detection in Twitter: The Role of Affective Content", Published in ACM Trans. Internet Techn. 2016.DOI:10.1145/2930663.

[20] Hana Alostad and Hasan Davulcu, “Directional Prediction of Stock Prices using Breaking News on Twitter”, IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology, 2015.

[21] Apoorv Agarwal, Boyi Xie, Ilia Vovsha, Owen Rambow and Rebecca Passonneau, "Sentiment Analysis of Twitter Data", Proceedings of the Workshop on Language in Social Media (LSM 2011), pages 30–38, Portland, Oregon, 23 June 2011. c 2011 Association for Computational Linguistics.