Nitha. K. P, Dr S Sivakumari

Turkish Online Journal of Qualitative Inquiry (TOJQI) Volume 12, Issue 6, June 2021: 1700-1707

Sentimental Analysis for Sensex Stocks using Vader Algorithm- An approach for Investment recommendations in Indian stock market

Nitha. K. P^a, Dr S Sivakumari^b

 ^{a*} Research Scholar, Department of Computer Science and Engineering, Avinashilingam Institute for Home Science and Higher Education for Women
^b.Professor and Head, Department of Computer Science and Engineering Avinashilingam Institute

for Home Science and Higher Education for Women

Abstract

There are different approaches to suggest investment strategies for the stocks in the stock market. Accurate prediction of investment strategy for stocks is one of the challenging tasks for an investor. This paper focuses on developing a model that supports stock market investment decision making strategies for Sensex stocks in India using sentimental analysis. In this study, we used an approach to predict the investment strategy through VADER Model. We claim that the sentiment analysis of news headlines and tweets has an impact on stock market values. So, news headlines are collected along with the stock market investment data for the period of study. The model, when used in Sensex, shows accuracy in the prediction of investment strategies.

Keywords: Sentimental analysis, Sensex, Classifier Model

1. Introduction

Sentiment analysis refers to an automated process of determining whether a piece of written information is positive, negative or neutral. It is also called opinion mining which is also referred to as the detection of subjective information such as opinions, attitudes, emotions, and feelings expressed by people in blogs, tweets, and comments. According to the search engine statistics and bright local survey, 92% of consumers trust online reviews as much as personal reviews. But still, there are several challenges for accurate sentiment evaluation such as difficulty in training the computer to understand human sentences or linguistics, evaluating sentiments concerning several properties, unavailability of a standard scientific lexicon for parameters or features, concerning the domain applied. Despite all these challenges, Sentimental Analysis, a natural language processing (NLP) technique used to classify biased information, is proved as one of the strongest and accurate techniques.

Sentiment analysis is a technique used to mine such opinion and remarks of users by classifying them as positive, negative, and natural. Sentiment analysis is a technique used to collect information based on the person's opinion from raw data available on the internet. The words used to express a sentiment are the most significant challenge we have while performing the

sentimental analysis.

The Machine Learning approach and Lexicon based approach are the two major classifications used in Sentimental Analysis.

A) **Machine Learning Approach** – This has been applied in the field of sentiment analysis, which is further divided into supervised and unsupervised learning methods. Supervised learning requires labelled classes and two sets of documents: a training set and a test set. The training set is used to learn different properties of documents, and the classifier test set is used to evaluate the performance.

2.Supervised Learning techniques

i) *Decision tree classifier* uses a hierarchical decomposition of training data in which data is divided based on the condition of attribute values.

Sentimental Analysis for Sensex Stocks using Vader Algorithm- An approach for Investment recommendations in Indian stock market

ii) *Rule-based classifier* is based on the rule on occurrences of emotions found in the text. If a word contains a positive texture, then it is considered positive, and if the word contains negative indications, it is considered negative.

iii) *Probabilistic classifier* is based on the prediction of input given probability distribution. Probabilistic classifiers are of two types which are Naïve bayes classifier and maximum entropy classifier. The naïve Bayes classifier is based on the Bayes theorem of the probabilistic model. In this method, the probability estimation of a text is performed to check whether it belongs to a positive or negative class. Maximum Entropy classifier is a probabilistic based classifier that belongs to the exponential model class.

iv) *Linear classifier* is the one that partition a set of objects into their respective cluster with a line, and if it is partitioned with a curve is called a hyperplane. There are two types of linear classifiers, which are support vector machine & multilayer neural network. In the area of classification and regression analysis, SVM is a supervised learning classifier widely used. The main idea of SVM is to determine the most fitting linear separator in the search space, which can separate the different classes.

3.Unsupervised Learning techniques

Unsupervised learning has no explicit target output or a labelled class associated with the input, and learning happens through observation. The goal is to make the machine learn without giving any explicit training. Clustering is one of the famous approaches in unsupervised learning, in which similarities of elements in the training data is found out.

3.1.Lexicon based approach

An assumption that the sum of the sentiment orientation of each word makes contextual sentiment orientation. There are two types which are dictionary-based approach and corpus-based approach. The dictionary Based approach uses a predefined dictionary of words where each word is associated with a specific sentiment polarity strength. The corpus-based approach tries To find co-occurrence patterns of words to determine their sentiments is the approach used in the Corpus-based technique. This approach is based on a list of opinion words and then find other opinion words which have similar context.

As the Indian Stock Market is suitable for making a profit to investors, it is important to know the buy and sell tips of different stocks using various techniques. There are different techniques used for giving suggestions to the investors on buy and sell actions of stocks. There exist errors in the buy/sell tips provided by brokers or software's to the investors due to the lack of scientific applications in analysis. This study is evaluating investment suggestions based on polarity score results and develop a new model using sentimental analysis that gives accurate suggestions on buy/sell actions using a machine learning approach for investment decisions in the stock market.

4. Review of Literature

Shri Bharathi, Angelina Geetha, attempts to design and implement a predictive system for guiding stock market investment. The novelty of the approach is the combination of both Sensex points, and Really Simple Syndication (RSS) feeds for effective prediction. An algorithm for sentiment analysis studied, the correlation between the stock market values and sentiments in RSS news feeds are established, and the trained model worked very well in predicting the stock prices. Sahar Sohangir, Dingding Wang, Anna Pomeranets and Taghi M. Khoshgoftaar used Big Data: Deep Learning to improve the performance of sentiment analysis for Stock Twits. The results show that the Deep Learning model can be used effectively for financial sentiment analysis, and a convolutional neural network is the best model to predict the sentiment of authors in the Stock Twits dataset. Zhaoyue Wang, Jinsong Hu, and Yongjie WuA studied Existing algorithms, including BP and many current algorithms, still could not provide helpful prediction results for stock investors. An important reason may be that stock data in a long period are too complex and include too many modes. Omer Berat Sezera,c, Murat Ozbayoglua1, Erdogan Dogdu used Deep Neural-Network Based Stock Trading System Based on Evolutionary Optimized Technical Analysis Parameters, proposed a stock trading system based on optimized technical analysis parameters for creating buy-sell points using genetic algorithms. The model is developed utilizing Apache Spark big data platform. The results indicate that optimizing the technical indicator parameters not only enhances the stock trading performance but also provides a model that might be used as an alternative to the Buy and Hold strategy.

Rajashree Dash, Pradipta Kishore Dash used a hybrid stock trading framework integrating technical analysis with machine learning techniques. This study has proposed a novel decision support system for developing efficient stock trading strategies, which may provide attractive benefits for investors. The model has integrated technical analysis with machine learning techniques for the efficient generation of stock trading

decisions. Adam Atkins, Mahesan Niranjan, Enrico Gerding studied financial news and predicted stock market volatility better than close price. Empirical results suggest that information extracted from textual news sources can be used in predicting directional changes in market volatility. In particular, changes in volatility are better predicted than the changes in the close price of an asset or an index of assets. Results suggest that information in the news influencing markets via sentiment-driven behaviour essentially affects second-order statistics of the financials.

Andrius Mudinas, Dell Zhang, Mark Levene studied the market Trend Prediction using Sentiment Analysis and investigated the potential of using sentiment attitudes (positive vs negative) and also sentiment emotions (joy, sadness, etc.) extracted from financial news or tweets to help predict stock price movements. Extensive experiments using the Granger-causality test have revealed that (i) in general, sentiment attitudes do not seem to Granger-cause stock price changes; and (ii) while on some specific occasions' sentiment emotions do seem to Granger-cause stock price changes, the exhibited pattern is not universal and must be looked at on a case-by-case basis. Furthermore, it has been observed that at least for certain stocks, integrating sentiment emotions as additional features into the machine learning-based market trend prediction model could improve its accuracy. Shantanu Pacharkar, Pavan Kulkarni, Yash Mishra, Amol Jagadambe, S.G.Shaikh using Sentiment Analysis shown that a strong correlation exists between rising/fall in stock prices of a company to the public opinions or emotions about that company expressed through reviews and news. The main contribution of this study is the development of a sentiment analyzer that can judge the type of sentiment present in the review. This study recommends investing in a company whose sentimental score is high and positive; there are high chances for its stock prices to go up in future.

Juhi Gupta, Anshul Jain, Yash Bohra used Sentimental Analysis on news data for stock market prediction. This study gave a platform and automated the task of the user of going through the news, current trends and historical price of the stock. After so much research in this area, finally, analyst came to the conclusion that the method of analyzing social data with historic price will give us good results like 80% accuracy. The project considers both the important aspect of news and historical price to predict the stock market movement. Marxian Oli. Sigo studied big data analytics application of artificial neural network in forecasting stock price trends in India. This paper analyses the nonlinear movement pattern of the most volatile, top three stocks in terms of market capitalization, listed in the Bombay Stock Exchange (BSE) in India, namely Reliance Industries Limited (RIL), Tata Consultancy Services (TCS) Limited and HDFC Bank Limited, using the Artificial Neural Network (ANN) for the study period from 2008 to 2017. The findings of the study would help the investors to make rational, well-informed investment decisions to optimize the stock returns by investing in the most valuable stocks.

5. Sources of data

The study used secondary data. Secondary sources include the news headlines extracted from moneycontrol.com and Twitter API. A total of 30 Sensex stocks constituting Sensex are selected for the study.

6. Tools used for the study

6.1.Descriptive Statistics

The results are summarized using descriptive statistics such as mean, standard deviation, median etc., for the polarity score using the sentimental model. Predictions were compared to the actual performance from 2008-09 to 2017-18, and percentage errors are calculated.

6.2.Softwares

To analyze the data, R Software 4.0.2 is used. The model is developed using the python platform.

6.3.Analysis

In this research sentiment value of the news headlines regarding each stock for ten financial years (2008-09 to 2017-18) is calculated, and its average is considered as sentiment value, i.e., the polarity of the stock to classification module.

The steps used in this module are as follows:

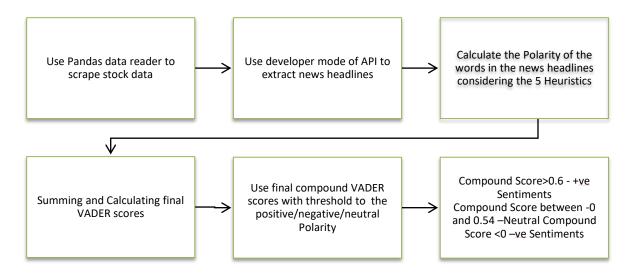


Fig 1.1 Steps for calculating the Polarity of the text using the VADER Algorithm

6.3.1.. Data Collection

The data is collected using the pandas' data reader to scrape news headlines from moneycontrol.com. The developer mode API of twitter.com is used to extract data from Twitter.

6.3.2. Calculating polarity of the headlines using the 5 Heuristics of the VADER Algorithm

Each news headline is broken down into sentences. Further the sentences are broken down into words to find the VADER scores based on the positive 'negative score as well as the intensity of emotions considering the following 5 heuristics:

• **Punctuations:** They increases the magnitude of intensity. For example, the sentence," The price is high !!!" with punctation exclamations increases the intensity of the sentences when compared to the sentence," The price is high".

• **Capitalization:** All letters of a word in caps usually emphasizes the sentiment relevant word. For example, consider the statements, "The price is HIGH and "The price is high". The word HIGH in the first sentence highlights the relevance of high price of the stock when compared to the "high" in the second statement.

• **Degree Modifiers:** The words like extremely, very, pretty, fairly are considered to impact the sentiment of sentences. For example, "The price is extremely high" intensifies the sentiment of the statement when equated to "The Price is high"

• **Conjunctions:** The use of constructive conjunctions like 'but', 'nor', 'so', 'or', 'yet, signals a shift in sentiment polarity, giving dominance to one part of the sentences. **"The price is high, but it is affordable"**, contrastive conjunction "but" used in the above sentence signals a shift in sentiment polarity, given dominance to the latter half

• **Polarity Negation:** The negations used in the statements has a tendency to flip the polarity/sentiments of the text. Also, a contiguous sequence of 3 words, preceding a sentiment-laden lexical feature and a negation also has more impact on the polarity of the statements." **The price isn't really that high**", in the above blog the actual polarity of the statement is positive, but if the 3 contiguous sequence of word "**really that high**" along with the negation "**isn't**" is not considered then it might be categorized as a negative statement.

c. Summing and Calculating the final VADER Scores

After calculating the individual scores of each word of the sentences the final scores are calculated as the average of the scores, and the polarity is determined by mapping them to the threshold value.

d. Mapping the final compound scores to the threshold, categorizing them as positive, negative and neutral

The next step is to map the compound scores to the threshold and find the polarity of the text. The following rules are used to identify the polarity

If the Compound Score>0.6 then the text highlights a positive sentiment,

If the Compound Score between -0.5 and 0.54 then it is considered to be Neutral,

If the Compound Score < -0.5 then the text gives a negative sentiment.

The compound polarity of the sentence is computed. This innovative approach is proposed to predict the buy or sell signal to the investors in the prediction of stock market analysis. In the proposed approach of stock market forecasting is achieved by taking the stock related RSS news feeds, Tips etc. Sentiment classification has become a very popular task in natural language processing area, which tries to predict sentiment (opinion, emotion, etc.) from texts. Sentiment classification done in word level, sentence level and document level. News feeds are collected from many reputable financial news sites in India. For sentiment analysis, only the text data of each news or article is used. All other attributes of the articles in the dictionary are dropped and sentiment analysis is performed using python's VADER API. This VADER API is a powerful lexicon-based sentiment analyzer which uses semantic information from multiple corpora to analyze the sentiment of each sentiment. This study does not require a training data set which is one of the advantages.

Table 1.1 shows the descriptive statistics of polarity score for 30 Sensex stocks which indicates the intensity and variability of sentiments, emotions, News prevailing in the market for Sensex stocks in Indian stock market from 2007-08 to 2017-18.

Name of stock	Minimum	Maximum	Mean	SD
Asian Paints	0.00	0.81	0.37	0.34
Axis Bank	-0.03	0.13	0.04	0.04
Bajaj Auto	0.00	0.29	0.17	0.08
Bajaj Finance	0.00	0.79	0.26	0.22
Bharathi Airtel	0.18	0.88	0.55	0.25
Coal India	-0.32	0.11	-0.04	0.14
HCL Tech	0.12	0.61	0.40	0.14
HDFC	-0.13	0.41	0.05	0.14
HDFC Bank	-0.03	0.08	0.03	0.04
Hero Motors	00.00	0.82	0.22	0.31
Hindustan Unilever	0.13	0.99	0.65	0.30
ICICI	0.05	0.29	0.15	0.07
IndusInd Bank	-0.14	0.27	0.07	0.12
ITC	-0.18	0.98	0.54	0.42
Kotak Mahindra Bank	0.00	0.15	0.08	0.04
Larsen & Toubro	-0.15	0.28	0.09	0.12
Maruti Suzuki	0.02	0.85	0.43	0.29
Mahindra & Mahindra	-0.72	0.70	0.18	0.40
NTPC	-0.30	0.30	0.00	0.14
ONGC	-0.34	0.42	0.04	0.20
Power Grid	-0.34	0.72	0.14	0.27
Reliance Industry	-0.02	0.36	0.13	0.12
SBI	0.00	0.06	0.03	0.02
Sun pharma	-0.30	0.30	0.00	0.14
Tata motors	0.00	0.13	0.05	0.05
Tata DVR	-0.25	0.40	-0.01	0.20
Tata steel	0.03	0.89	0.33	0.25
TCS	-0.10	0.38	0.07	0.14
Vedanta	-0.32	0.03	-0.14	0.11
YES Bank	0.00	0.45	0.28	0.12

Table1.1 Descriptive statistics of Polarity score for Sensex stocks

High Mean value of polarity score for Asian paints, Tata steel, Bharathi airtel, ITC and Hindustan Unilever tell the positive sentiments, news and prospects of the company for the last ten years. The highest mean shows the confidence of investors to remain with the same company. Minimum polarity score of Mahindra & Mahindra

Sentimental Analysis for Sensex Stocks using Vader Algorithm- An approach for Investment recommendations in Indian stock market

indicates most negative news and sentiments taken place for the same company in one year. Maximum polarity score of ITC, HUL indicates most positive news and sentiments taken place for the same company in one year. The extreme value of standard deviation of polarity score shows the variability of sentiments for Mahindra & Mahindra and ITC.

Table 1.2 represents the Polarity of the Sensex stocks for the Financial Years from 2008-09 to 2017-18 and the sentimental indicators given to the investors along with stock returns to know the prediction accuracy of the model. Table focused on the mean of positive score, negative score and neutral score of Polarity score respectively based on the sentiments taken from the market. Overall emotions, both at the level of groups of traders and investors at wider society, are influencing the behavior of financial markets.

This study proven that, there is no similarity between negative and positive sentiments score which suggests that Sensex stocks carry more positive sentiments in the market for last ten years. Sentiments of stocks such as Asian paints, Bharathi Airtel, Hero motors, HUL and ITC respectively are highly positive which influenced the short-term price movement in favor to the investors. However, the mean value of negative polarity score for Coal India, NTPC, Sun pharma, Mahindra & Mahindra, Vedanta indicates the negative sentiments of these stocks in the market. This adversely effect on the short-term price movement for these stocks. This average polarity score calculated for the last ten years can be used as reference by the traders to trade in the above Sensex stocks on short term basis. It was found that sentimental model that resulted with smallest prediction error that can give the accurate prediction of investment strategies in stock market. This proved that VADER algorithm is quicker than other method in prediction.

Based on percentage analysis, it was found that this approach works very well for Sensex stocks in Indian stock market for short term prediction purpose. The mean accuracy percentage of this model is 80 % states that prediction accuracy is at high level in predicting the short term and long-term investment suggestions for Sensex stocks. It is also noted that there is 100% prediction accuracy for 17 stocks and remaining 7 stocks also shown 66% accuracy in prediction. Axis bank, Bajaj Auto, Bajaj finance, HCL Tech, HDFC, HUL, ICICI, INDUSIND, ITC, Kotak Mahindra Bank, L&T, Sun pharma, Tata DVR, Tata steel, Vedanta have got 100 % accuracy in predicting the short-term investment and long-term Investment decisions under the sentimental analysis.

	Suggestions by Sentimental Approach Mean of Polarity					Returns & Prediction Accuracy			
Stocks						Weekl			Accurac
	Positive	Negative	Neutral	Compoun d	Suggestio n	y y	Monthly	Yearly	y y
Asian Paints	0.52	*	0.03	0.52	Buy	-3.90	-90.12	35.63	33
Axis Bank	0.09	*	0.02	0.11	Buy	8.56	1.65	40.07	100
Bajaj Auto	0.18	*	0.15	0.33	Buy	0.26	3.70	3.21	100
Bajaj Fin	0.26	*	0.00	0.26	Buy	5.85	2.50	60.46	100
Bharathi	0.59	*	*	0.59	Buy	0.28	5.06	-17.41	66
Coal India	0.09	-0.24	0.02	-0.13	Sell	6.58	5.76	-13.99	66
HCL Tech	0.16	*	*	0.16	Buy	4.21	5.15	17.78	100
HDFC	0.20	-0.13	0.00	0.07	Buy	0.61	8.88	14.99	100
HDFC Bank	0.08	*	0.01	0.09	Buy	-0.34	2.06	17.55	66
Hero Motors	0.64	*	0.00	0.64	Buy	28.57	28.01	-10.87	66
HUL	0.66	*	*	0.66	Buy	2.31	12.10	27.01	100
ICICI	0.17	*	0.16	0.33	Buy	13.64	9.09	53.50	100
IndusInd	0.16	-0.06	0.01	0.11	Buy	5.40	4.77	4.01	100
ITC	0.70	-0.18	0.02	0.54	Buy	0.55	6.94	16.12	100
Kotak	0.09	*	-0.01	0.08	Buy	5.44	14.05	25.22	100
L& T	0.15	-0.15	0.00	0.00	Hold	3.37	6.29	8.09	100
Maruti	0.51	*	0.02	0.49	Buy	3.01	1.72	-22.15	66
M & M	0.39	-0.72	0.00	-0.33	Sell	3.04	3.96	-13.70	33
NTPC	0.30	-0.32	0.00	-0.02	Sell	-0.14	0.54	-0.79	66
ONGC	0.36	-0.34	0.03	0.00	Buy	0.56	1.11	-12.82	66

Table 1.2 Polarity of the Sensex stocks for the Financial Years from 2008-09 to 2017-18

Nitha. K. P, Dr S Sivakumari

Power Grid	0.26	-0.18	0.17	0.25	Sell	1.11	5.92	-1.02	33
Reliance	0.17	-0.02	0.03	0.18	Buy	3.85	3.19	44.50	100
SBI	0.06	*	0.02	0.08	Buy	-2.73	-5.46	22.88	33
Sun pharma	0.30	-0.35	0.00	-0.05	Sell	-0.63	-1.28	-16.60	100
Tata motors	0.05	*	*	0.05	Buy	2.83	-1.89	-57.15	33
Tata DVR	0.12	-0.14	-0.05	-0.07	Sell	-0.56	-5.04	-55.42	100
Tata steel	0.36	*	0.03	0.33	Buy	4.43	6.09	0.55	100
TCS	0.26	-0.01	0.03	0.28	Buy	4.81	12.52	38.52	100
Vedanta	*	-0.19	0.03	-0.16	Sell	-1.33	-0.62	-37.71	100
Yes Bank	0.32	*	-0.01	0.31	Buy	0.79	11.11	-14.22	66
Overall accuracy of sentimental analysis in prediction of Investment strategy								80	

This study developed a sentimental model using market sentiments to take an investment decision for Sensex stocks in Indian Market. Analysts and portfolio managers typically cover a long list of stocks for buying and selling purpose. This study helps to increase their efficiency of screening stocks with a powerful and simple framework to choose Sensex stocks using Sentimental Analysis Model based on Polarity score. Indian Stock Market is more volatile due to the sentiments that effect the changes in the value of Sensex stocks which will assist investors for short term investment decisions in the stock market through sentimental analysis for short term investment decisions in the Indian Stock Market.

References

- [1] Shri Bharathi, Angelina, (2017), Sentimental analysis for effective stock market prediction, International journal of intelligence and engineering systems, 146-154
- [2] Sahar Sohangir1*, D. W. (2018). Big Data: Deep Learning for financial sentiment analysis. Journal of big data, 1-25.
- [3] Zhaoyue Wang, J. H. (2018). A Bimodel Algorithm with Data-Divider to Predict Stock Index. Hindawi-Mathematical Problems in Engineering, 1-14.
- [4] Omer Berat Sezera, c. M. (2017). A Deep Neural-Network Based Stock Trading System Based onEvolutionary Optimized Technical Analysis Parameters. Procedia Computer Science, 473-480.
- [5] Subashini1, D. M. (2018). Forecasting on Stock Market Time Series Data Using Data Mining Techniques. International Journal of Engineering Science Invention (IJESI), 6-13.
- [6] Adam Atkins*. (2018). Financial news predicts stock market volatility better than close price. The journal of finance and data science, 120-137.
- [7] Maree, S. (2015). CRITICAL INSIGHTS INTO THE DESIGN OF BIG DATA ANALYTICS RESEARCH: HOWTWITTER "MOODS" PREDICT STOCK EXCHANGE INDEX MOVEMENT. The African Journal of Information and Communication, 53-67.
- [8] Mehta, J. (2015). Big Data Analysis of Historical Stock Data Using HIVE. ARPN Journal of Systems and Software, 40-43.
- [9] Rajashree Dash a, *. P. (2016). A hybrid stock trading framework integrating technical analysis withmachine learning techniques. The Journal of Finance and Data Science, 42-57.
- [10] Madge, S. (2015). Predicting Stock Price Direction using Support Vector. Independent Work Report Spring 2015, 1-8.
- [11] Sigo, M. O. (2018). BIG DATA ANALYTICS-APPLICATION OFARTIFICIAL NEURAL NETWORK IN FORECASTINGSTOCK PRICE TRENDS IN INDIA. Academy of Accounting and Financial Studies Journal, 1-13.
- [12] Shantanu Pacharkar1, P. K. (2018). Predicting Stock Market Investment Using Sentiment Analysis. International Journal of Advanced Research in Computer and Communication Engineering, 109-114.
- [13] Bhardwaja, A. (2015). Sentiment Analysis for Indian Stock Market Prediction UsingSensex and Nifty. Procedia Computer Science, 85-91.

Sentimental Analysis for Sensex Stocks using Vader Algorithm- An approach for Investment recommendations in Indian stock market

- [14] Bhavya Kaushik, H. H. (2017). Social media usage vs. stock prices: an analysis of Indian firms. Procedia Computer Science, 323-330.
- [15] Chowdhury, S. G. (2014). News Analytics and Sentiment Analysis to PredictStock Price Trends. International Journal of Computer Science and Information Technologies, 3595-3604.
- [16] Das, S. (2018). Real time sentiment analysis of twitter streaming data for stock prediction. Procedia Computer Science, 956-964.
- [17] Ding, X. (2013). Deep Learning for Event-Driven Stock Prediction. Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence (IJCAI 2015), 2327-2333.
- [18] Jangid, H. (2018). Aspect-Based Financial Sentiment Analysis using Deep Learning. Track: Challenge #4: Multi-lingual Opinion Mining, 23-27.
- [19] Khedr, A. E. (2017). Predicting Stock Market Behavior using Data Mining Technique and News Sentiment Analysis. I.J. Intelligent Systems and Applications, 22-30.
- [20] Kollintza-Kyriakoulia, F. (2018). Measuring the Impact of Financial News and SocialMedia on Stock Market Modeling Using Time Series. Algorithms, 1-24.
- [21] Kollintza-Kyriakoulia, F. (2018). Measuring the Impact of Financial News and SocialMedia on Stock Market Modeling Using Time SeriesMining Techniques. Algorithms 2018, 1-24.
- [22] Lee, Y. (2017). Stock Prediction and Prediction Accuracy Improvement using Sentiment Analysis and Machine Learning based on Online News. Proceedings of the International Conference on
- [23] Mudinas, A. (2018). Market Trend Prediction using Sentiment Analysis:Lessons Learned and Paths Forward. WISDOM'18, August 2018, London, UK, 1-14.
- [24] Nausheen S, A. K. (2015). SURVEY ON SENTIMENT ANALYSIS OF STOCK MARKET. International Journal of Research - GRANTHAALAYAH, 69-75.
- [25] Pagolu, V. S. (2016). Sentiment Analysis of Twitter Data forPredicting Stock Market Movements. International conference on Signal Processing, Communication, Power and Embedded System, 1-10.
- [26] Patel, R. (2016). Stock Market Prediction Using Sentiment Analysis: Testing The Method"s Accuracy and Efficiency. International Journal of Latest Technology in Engineering, Management & Applied Science, 143-145.
- [27] Ramteke, P. K. (2018). Stock Market Prediction Using News Feed and Historical Data. IJARIIE, 2395-4396.
- [28] Rupawari Jadhav1, M. S. (2017). Survey : Sentiment Analysis of Twitter Data for Stock Market Prediction. International Journal of Advanced Research in Computer and Communication Engineering, 558-562.
- [29] Skuza, M. (2015). Sentiment Analysis of Twitter Data within Big Data DistributedEnvironment for Stock Prediction. Proceedings of the Federated Conference on, 1349–1354.
- [30] Umamaheswari, K. (2018). Stock Market Predictor and Analyser usingSentimental Analysis and Machine LearningAlgorithms. International Journal of Pure and Applied Mathematics, 5395-15405.
- [31] . Wang, C. (2019). Novel Approaches to Sentiment Analysis for Stock Prediction. Github repository, 1--12.