Study of Recent Advances in Sentiment Analysis for Stock Prediction

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Abstract

The prediction and speculation about the values of the stock market, especially the values of the worldwide companies are a really interesting and attractive topic. In this article, we cover the topic of the stock value changes and predictions of the stock values using fresh scraped economic news about the companies. We will be using various kinds of NLP techniques to find the sentiment of a news headline. With use of these techniques we will be generating sets of results. On comparing these results with the movement of stock market values in the same time periods, we can establish the moment of the change occurred in the stock values with sentiment analysis of economic news headlines. Also we discovered a significant difference between the different models in terms of the effect of emotional values on the change in the value of the stock market by the correlation matrices.

Keywords Deep Learning · Neural Networks, Augmented Textual Features, Sentimental Context, BERT, NLPTK, VADER, Big Data, financial sentiment analysis, stock market prediction, word embedding methods, Price forecasting, sentiment analysis, CNN, SVM, ANN, NSE, BSE, financial market, Data mining,Reinforcement learning Portfolio allocation, Stock prices, Sectoral outlook, Market sentiment, Wavelet coherence and correlation, Machine learning, contextual sentiment analysis, sentiment contagion, implicit sentiments, volatility, investor sentiment, stock return

1. Introduction

1.1 Problem definition

Fundamental theories of finance like mean variance analysis of Markowitz (1952) points out that the rational behaviour of investors and market fundamentals is believed to be the sole factor that plays a decisive role in shaping the decision of investors in the stock market [6]. According to them the whole stock market can be predicted using the Mean Variance theory. Mean Variance theory works on pure mathematics, but when it comes to stock prediction there is one more factor called sentimental context. Every trader has a sentiment analysis before buying a stock. The opening and closing price of every stock depends on the sentiment of the trader towards the stock.

Stock market is a highly volatile place where a stable stay can never be experienced [1]. Thus to bear with the volatility we need to predict the stock. Thus here comes Sentiment Analysis. As discussed above, a trader has hundreds of sentiments before buying a stock. No trader buys a stock without a motive and when we talk about this sentiment it's all derived through news headlines, tweets, paper headlines etc. Thus these headlines and tweets create a huge impact on stock price [2]. People tend to believe what they see, and with news and paper headlines being in favour of a company makes people buy their stocks and vice versa. Thus these headlines get woven with the companies without physical existence.

From these given points we would be defining how sentiment analysis plays a vital role in prediction of stocks rather than the old technique of Mean variance by the end of the paper.

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1.2 Impact

With the prospect of what we are believing and trying to point out we believe the stock market prediction can be improved by 60% [3]. Relying on the old theory of Mean Variance and applying the same theory on every stock is not an ideal solution. Every stock has its own state of volatility and non linearity. Considering them all the same and applying the same theory may lead to false results. Thus we need some solution which can be unique for every stock and predict it with higher precision.

Sentiment analysis works on headlines denoted for individual stock or company. With focus in particular stock we can derive results which are highly precise and accurate. Thus adopting the method of sentiment analysis can create a huge impact on stock prediction.

1.3 History of Problem

History of the problem started when people considered stocks only as a market of mathematics. It's not all about mathematics in stock prediction. The early fundamental theories of finance believe in the theory of Mean Variance. Fundamental finance believes the stock market can be completely predicted using Mean Variance theory. Applying the same theory on every Stock can provide them an accurate result. But it's not true, with every stock purchase every trader has their own sentimental context behind it. The sentimental context can be due to any reason.

This application of fundamental theory on every stock is the root cause of irregularity in stock prediction. We need a firm process which can get the best precision possible for predicting stock. Not only this, people generally believe in past day prediction, which means predicting stock on the performance given on previous days. This theory is also wrong, we can't and could never judge a stock with just past performance of a couple of days. We need a firm set of data to conclude with this theory.

These are the root causes, why we need a new technique to predict the stock market.

1.4 Different approaches taken by researchers

The different approaches which were used in the papers were wavelet analysis, different machine learning models like random forest, gradient boosting genetic algorithm **[7]**, Fine tuned textual representation **[8]**, deep learning models like LSTM (Long Short Term Memory) **[2][3][9]**, adaptive sentiment-aware deep deterministic policy gradients approach **[10]**, convolution neural networks (CNN) **[3][11][12]**, recurrent neural networks **[12]**, deep learning algorithms and Word2Vec, GloVe, and FastText. In other papers sentiment analysis was done using BERT techniques **[1]**, graph based semi supervised learning and autoregressive conditional heteroscedasticity (GARCH) models **[6]** were used. Recurrent neural networks (RNN) was also seen to be used in some of the papers **[1][2][9][12]**. Apart from these certain models like NLTK Vader Lexicon, Text Blob **[1]**, Panel regression model, Fama French Model **[4]**, Logistic regression model, Linguistic rule-based model, graph-based semi-supervised learning **[5]**, Principal Component Analysis (PCA), SKlearn feature extractor **[6]**, were seen to be used. And lastly Deterministic Policy Gradient, or DPG and DDPG **[10]** were also used.

1.5 Purpose of this paper

In This survey paper we are going to compare and discuss different methods of sentiment analysis in order to predict the stock market and share prices of a company. We will be exploring the most recent trends in the field of stock prediction and discuss the improvements and advancements in performance and development of models that improve the prediction of stock prices for maximum profit.

The main purpose of this paper is to compare different papers and their algorithms on the problem“stock prediction using sentiment analysis NLP” and then to come up with the best algorithm among all these algorithms. For this we collected the recent research and also used different existing research to compare the methodology in the architecture.Our main research involved analysing the social media data and news data to predict the stock value. Our main objective was to solve stock portfolio allocation and maintain it to get maximum return with minimum risk involved[10] and to analyse stock value changes and predictions of the stock values using fresh scraped economic news about the companies[1].

We analysed Japanese news and the impact of COVID 19 to come up with good investment strategies in various stock exchanges[2][4]. Opinion Mining and graph based Sentiment analysis were the common approaches to predict the stock values[5].

1.6 Document layout

The flow of the survey paper is as follows:

- Firstly this survey paper gives an introduction about this paper.Then we discuss the importance and uses of sentiment analysis, what sentiment analysis can do, how it can help people and the company to predict the stock values for maximum profit involving minimum risk..

- Then, we discuss the architecture of sentiment analysis for stock market prediction.
- Then, we will discuss the evaluation methods which we encountered across different papers.
- Then, section 4 details the popular evaluation methods and datasets used in the base papers.
- A comparative analysis of the base papers has been included in section 5.
- Section 6 contains the conclusion and future work.

2. Definition of Important of Terms

1. Stock Prices : Stock means equity of an organisation which is divided in several parts.Stock price means the current price of the stock that is trading for in the market.
2. Sectoral Outlook : It means the trend of different industries in the financial sector.
3. Market Sentiment : Market sentiment means the overall trend or the behaviour of investors towards a particular market in the financial market.
4. Wavelet Coherence and correlation : Wavelet coherence refers to the measure of the correlation between two signals. It is used to measure linear interactions.
5. Machine learning : ML is a branch of Computer Science which concerns the study of various algorithms in order to improve the experience of computers and machines with the help of large samples of data.
6. Contextual sentiment analysis : It is related to gathering user data and analyzing it to form an opinion on a particular topic, which will be either positive or negative or neutral.
7. Sentiment contagion : sentiment contagion or emotion contagion refers to the process of observing behavior changes in an individual, which results in a similar behaviour in other individuals.
8. Implicit sentiments : Implicit sentiments refer to the expressions which are related to an idea without explicitly stating them, and they convey factual information which leads to a positive, negative or neutral response towards that idea.
9. Data mining: The practice of analysing large databases in order to generate new information.
10. Portfolio allocation: spreading the investments across various asset classes. Broadly speaking, that means a mix of stocks, bonds, and cash or money.
11. Sentiment analysis: contextual mining of text which identifies and extracts subjective information in source material, and helps a business to understand the social sentiment of their brand, product or service while monitoring online conversations.
12. Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems.
13. A Convolutional Neural Network (CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other.
14. NSE and BSE are stock exchanges of India. National Stock Exchange and Bombay Stock Exchange.
15. Volatility is the degree of variation of a trading price series over time, usually measured by the standard deviation of logarithmic returns
16. Stock return is the total return for a stock includes both capital gains/losses and dividend income, while the nominal return for a stock only depicts its price change

3. Architecture and analysis

The method that every model uses to find sentiments is called the Scoring technique. In this method tags are provided with a score. Withe score generated for a sentence the sentiment is predicted. Thus for every sentiment analysis to work on a sentence a scoring system is to be established, which scores a word according to the Language Processing model. The tagging technique which we use is shown below

Tags	Point
Positive	+1

Negative	-1
Neutral	0

For better understanding let's take an example and understand how the whole scoring technique works.
For eg:

1. **“Great bid to go with”** in this statement Great is a positive statement remaining are statement compositions.

   Thus, Total Score = +1, thus this statement is declared as **Positive**.

2. **“Great bid but can make loss too”** here in this statement Great is positive and loss is negative.

   Thus, total score = +1 -1 = 0, thus this statement is a **Neutral** statement.

3. **“Will lose price”** in this statement lose is a negative word and the remaining are statement compositions

   Thus the Total Score = -1, thus the statement is declared as **Negative**

This is how the basic architecture detects the sentence.

This way every sentence is parsed and provided with a score, and at the end if the score is Positive then there are high chances of increase in price of that stock and if negative then high chance of fall in price.

3.1 Prediction of stock values changes using sentiment analysis of stock news headlines [1]

a) Aim

Stock Prediction is one of the sectors where no one can achieve 100% efficiency. When it comes to prediction of stock it’s really tough since dynamics of stock market change in seconds. With such volatility it's really hard to predict it. But what we can do is try our best to get the best possible precision. Prediction of stock is directly dependent on the moves taken by companies and trader nature towards the company. Thus predicting it with company moves is not possible. So we will be predicting it in accordance to the trader/public nature towards the company. ANd the best source to get the nature of people towards companies is through news headlines.

b) Methodology and Results

Predictions of the stock values using fresh scraped economic news about the companies. With focus on the recent fresh news and using tools like, BERT as the baseline and compare the results with three other tools, VADER, TextBlob, and a Recurrent Neural Network, and compare the sentiment results to the stock changes of the same period.

The BERT and RNN were much more accurate; these tools were able to determine the emotional values without neutral sections, in contrast to the other two tools. Comparing these results with the movement of stock market values in the same time periods, we can establish the moment of the change occurred in the stock values with sentiment analysis of economic news headlines. Also we discovered a significant difference between the different models in terms of the effect of emotional values on the change in the value of the stock market by the correlation matrices **[18]**.

c) Advantages

With the proposed conclusion we came to know that there is no neutral emotion in sentiment analysis. This is because every sentiment caused an impact on the market. Thus while classifying the contextual texts we can eliminate the neutral emotion. This will help to improve the precision of prediction. Since now we have only two emotions to take care of. Thus every headline would give a direct result of positive or negative. This study eliminated the existence of a third emotion which directly helped in increasing the precision of the result **[13]**.

d) Disadvantages

Since this analysis was done on a small corporus it is not that evident if this proposed change will help in increasing the precision of result. Testing it on a wide variety of corpora and with a variety of techniques can only conclude what is the change in result derived. Thus considering it in such an early stage is not a good move. We need to have further experiments which can prove the existence of this conclusion. By the time we can only consider it as a prospect and avoid it from getting generalised.

3.2 A Method of Using News Sentiment for Stock Investment Strategy

a) Aim

The aim over here is to predict daily, weekly as well as monthly stock movement Stock exchanges. The study focuses on getting a universal method to predict stocks for desired period of time, which practically is impossible. As discussed the movement of stock price is directly dependent on company moves and nature of traders towards the company. So with such volatile proportionality we can't predict the stock for more than 2-3 days of time. So in order to check if it's possible or not this study was done.

b) Methodology and Results

The methodology is quite simple over here. The system uses a set of deep learning techniques to identify stock prices. Once the stock price list is obtained according to sentiment analysis then the obtained result is plotted on a graph. Now we will be comparing the graphs generated by sentiment analysis and economical graphs obtained by daily market value.

Thus we will be comparing and finding the common points, regular patterns etc to prove sentiment analysis is as good as economical prediction and most of the times better than too.

c) Advantages

This process makes the process really easy to find. With the usual process we need to read each line and give a verdict. But with this every line is parsed and a score is generated along with its sentimental context. This method can be applied on any model and it is really versatile to use. The method can be applied and adopted by any corpora and predicts a result with the same precision **[19]**.

d) Disadvantages

The issue lies over hee is the whole method was found to be short adopting. Like the effect of this method on any company will be short lived. This method is best suitable for daily trading, when it comes to long term trading or mid term this method seems to be a false case. The reason is very simple since the volatility of the market is dependent on the company moves and trader nature. Thus for short trading this method seems best case.

Other than that the method we adopted provides three emotional contexts(i.e Positive, Negative, Neutral), but with our study we found every news creates an impact on Stock price, so considering a stock headline as neutral and declaring it to have no impact on the stock price is wrong.

3.3 Augmented Textual Features-Based Stock Market Prediction

a) Aim

There is a high volatility, non-linearity and complexity in stock market prediction. It's inherently difficult to predict the Stock market due to its volatility. With the explosive non linearity predicting a stock seems really tough and unreal. So the aim is to predict the stock price using consumer behaviour and nature. Analysis of customer/trader behaviour towards a company can help to identify how well a stock can perform. Taking the top 10 companies of NASDAQ will help to generate more precise results, since those companies are always in headlines. Consuming data from such companies is really helpful for experimenting.

b) Methodology and Results

They proposed a methodology that starts by extracting multiple text-based features to enrich the representation of sentiments. Then it applies diverse feature selection methods to contextually choose the appropriate feature sets for different circumstances, and ends by stacking individual models to get the best of base stock direction classifiers **[13]**.

In the empirical investigation, different machine learning algorithms and feature selection methods performed differently for various stocks, which would not be the case if the stock market had followed a random pattern. We conclude that rise-and-fall in stock prices of a company is affected by the public opinions or emotions expressed. Only we need more sophisticated ways of sentiment analysis to predict the stock market direction **[23]**.

c) Advantages

The advantage of this method is it's easy to adopt on other corpus too. With its empirical investigation process things get really sorted out and finding a genuine prediction is really easy and precise. Along with that it was observed certain stock prices followed a regular pattern. Thus getting such patterns will help to make prediction easy for the next time, since those stocks have a regular pattern. Such patterns are hard to find if we go on with the random charts **[14][15]**.

d) Disadvantages

As mentioned, getting a pattern is really helpful but recurring of the same pattern in future is doubtful. So trusting such a pattern without solid proof may lead to wrong judgement. Thus before adopting a pattern we need to know the recurring of such patterns again is negligible sometimes **[16]-[18]**.

3.4 The impact of COVID-19 on the Chinese stock market: Sentimental or substantial?

a) Aim

Most researchers have observed plummets during the pandemic, but the reasons remain unclear **[24].** The aim of this paper is to show whether the impact of COVID-19 on the Chinese market was caused due to sentiments of the stock owners or due to substantial reasons. Because of the pandemic it was observed that the market had high volatility. A rational explanation for the volatility would be substantial economic loss according to the efficient market hypothesis. If it holds, the region with more confirmed cases would suffer more substantial losses. Naturally, the profitability of companies in that area would be weakened, and their stock returns would decrease **[4].** But it was observed that the rational reasoning did not stand and no such abnormal change was observed.

This paper goes ahead to show how sentiment contributes to the volatility of the stock market. They put forth 2 main hypotheses to test the contribution of sentiment:-

- The event that leads to strong negative sentiment, such as panic and anxiety. Previous studies argued that public health hazards such as SARS and Ebola can affect market sentiment. In the case of COVID-19, Liu, H. found that the virus outbreak had raised investors' fear of uncertainty **[25]**. Baig, A. S., Butt, H. A., Haroon, O., & Rizvi, S. A. R. found that the overall sentiment declined during the pandemic **[26]**

- The event caused lower yields on related stocks than usual.They said that media coverage of pandemics had an impact on the stock prices of companies closer to the origin area and in the pharmaceutical industry.

b) Methodology and Results

The authors broke down their methodology into main parts:-

- Event Study
- Panel regression

They have first calculated the abnormal returns of the stock market during the pandemic and conduct a significance test by doing an event study. Then, they went on to explore whether sentiment is explanatory to abnormal returns by regression.

The event study was done so as to identify abnormal returns in the stock market due to the outbreak of COVID-19. To do this they have divided their data on the basis of time to create event windows which can be seen in **Fig 3.4**. They have used the Fama- French Model to derive their expected returns and cumulative abnormal returns.

The result of the event study can be observed in 3 divided segments as follows: -

- After the event day => stock returns and individual sentiment both react negatively
- During event window => the standard deviation increases, leading to stock market yield decreasing and increase in volatility
- Post event window => the return and investor sentiment both rise, higher than normal before the pandemic outbreak
- Reversal effect was also observed

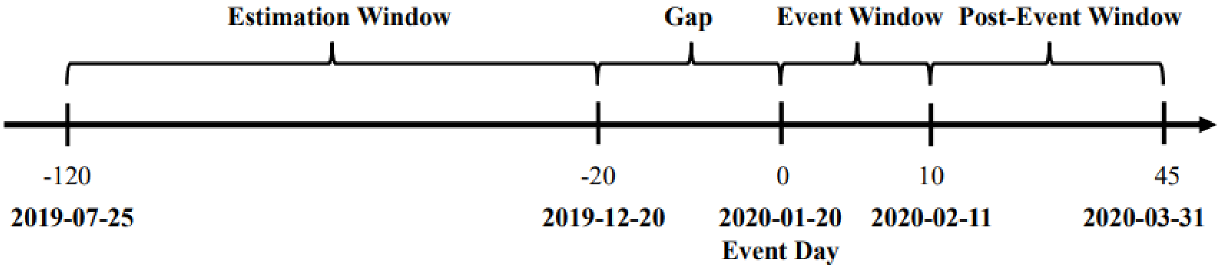


Fig 3.4: Set up of the Event Study

As compared to the event study, panel regression is better at capturing the time varying relationship between dependent and independent variables due to its ability to extract changes from panel data and minimize estimation bias. Therefore, panel regression is used to control heterogeneity during estimation of the sentiment effect **[4]**. Feasible generalised least squares(FGLS) was also done to ensure robustness of results.

The result of panel regression observed was as follows: -

- results show that the overall market return was significantly affected by sentiment
- Reversal effect was also observed meaning the stock returns depreciated during post-event window

c) Advantages

The advantages of the proposed work are that they have used event study and panel regression implying that they have tested their data over a period of time to give a proper solution which is helpful for performing sentiment analysis.

d) Disadvantages

This paper is mainly focused on only 7 main industries so this cannot be used as a basis for other industries.

3.5 Detecting a Risk Signal in Stock Investment Through Opinion Mining and Graph-Based Semi-Supervised Learning

a) Aim

A global economic crisis arose from the subprime mortgage crisis of 2008, resulting in corporate bankruptcies or delistings from securities markets amid a shrinking national economy **[27]**. If these minor occurrences can be identified and addressed in advance, a potentially catastrophic national or global crisis can be avoided.

The goal of this study is to use opinion mining and graph-based semi-supervised learning to create an algorithm to aid in stock investment decision-making **[5]** to avoid credit events that might cause a national and global economic crisis ultimately leading to socioeconomic losses.

The sentiment analysis used in this paper analyzes emotions expressed by people as a subfield of opinion mining and has recently been used in many fields of application, including the financial field **[28]** while, Semi-supervised learning has considerably better efficiency and accuracy than the abovementioned techniques since the number of independent variables is sufficient while the number of dependent variables is insufficient (a general situation) **[29]**

In order to complete their objective they have divided the processes involved as follows: -

- filtering fake information,
- assessing credit risk and detecting risk signals,
- predicting future occurrences of credit events through sentiment analysis, word2vec, and graph-based semi-supervised learning **[5]**

b) Methodology and Results

In order to evaluate the core processes following methods were used: -

- Filtering of fake information was done with the help of author analysis and a rule-based approach
- Credit risk was assessed with the help of opinion mining and sentiment analysis
- A signal for a credit event was then detected by the degree of assessed risk
- Predicting future occurrences of credit events was done based on the risk signal using logistic regression.

When investors are concerned about trading in a company's stock, a risk signal is characterised as a warning that they should pay attention to the company's status and management issues.This paper presents a a new method to recognise risk signals and anticipate the future occurrence of credit events to aid the decision-making process in stock investment.

This paper uses naive-Bayes classification, word2vec, and graph-based semi-supervised learning to propagate the sentiment value of core keywords to relevant words after allocating sentiment value for each text. To estimate credit risk, all textual material is preprocessed by natural language processing once it has been filtered for bogus information. After detecting the sign of a credit event, logistic regression is used to forecast the likelihood of a credit event occurring. The logistic regression prediction model is made up of sub-indices for assessing risk in the first phase.

The regression line made it possible to predict the occurrence of credit events by using events occurring in recent times. The credit event's projected occurrence was then compared to the actual occurrence.If the probability calculated using a regression line based on significant factors is greater than the threshold value, credit occurrences are more likely to occur.

c) Advantages

Our article handles false information from the perspective of data processing since the stock market is impacted by investor information, and there is a lot of it regardless of honesty. As a result, based on a vast quantity of opinion data, we presented an algorithm for recognising risk signs early. By presenting a method for when investors decide whether or not to trade stocks, our work increased the availability of social data in the finance market. Semi-supervised graph-based learning aids in the situational learning and classification of words or texts. Other data is smoothed and consistent with the labelled data using graph-based semi-supervised learning

d) Disadvantages

Despite the fact that each company is required to provide information about its financial health and significant changes in operations and management, some companies may conceal their unfavourable position. As a result, certain events are not visible or are concealed, making it harder to discover these hidden occurrences, which might result in a significant loss.

3.6 Sentiment Analysis of Indian Stock Market Volatility

a) Aim

The aim of this paper is to show how traditional empirical models (which analyze the impact of sentiments on financial market volatility using financial indicators or macroeconomic fundamentals.Further, the paper aims at proposing an augmented version of asymmetric GARCH model of conditional volatility for Indian stock exchange **[6].**

Fundamental theories of finance like mean variance analysis of Markowitz (1952) posits the rational behaviour of investors and market fundamental is believed to be the sole factor that plays a decisive role in shaping the decision of such investors **[30]**. During their study of literatures they found that, unlike rational investors, noise traders impact market return and volatility due to their cognitive errors and emotional exuberance **[31]**. This paper aims to enhance the statement, 'Sentiment is conceptualized as the overall attitude of an investor towards the market or any specific stock and this is independent of market fundamentals' by Atoniou **[32]**

b) Methodology and Results

The research takes a different method to modelling conditional volatility by employing basic macroeconomic or financial variables as sentiment components to determine their impact on market conditional volatility. To quantify different forms of attitudes in the Indian market, we used a novel approach of leveraging news driven sentiment research and augmenting volatility models with such sentiment factors.

Here they have implemented a GARCH model which is a statistical model that may be used to examine a variety of financial data, such as macroeconomic data. This model is commonly used by financial organisations to estimate the volatility of stock, bond, and market indices returns.

They have used NLP to find sentiment over their data following the steps in Fig 3.6.

Empirical findings suggest dominant impact of negative market sentiment over positive one and it also provides evidence of noise trading in financially immature Indian stock market.

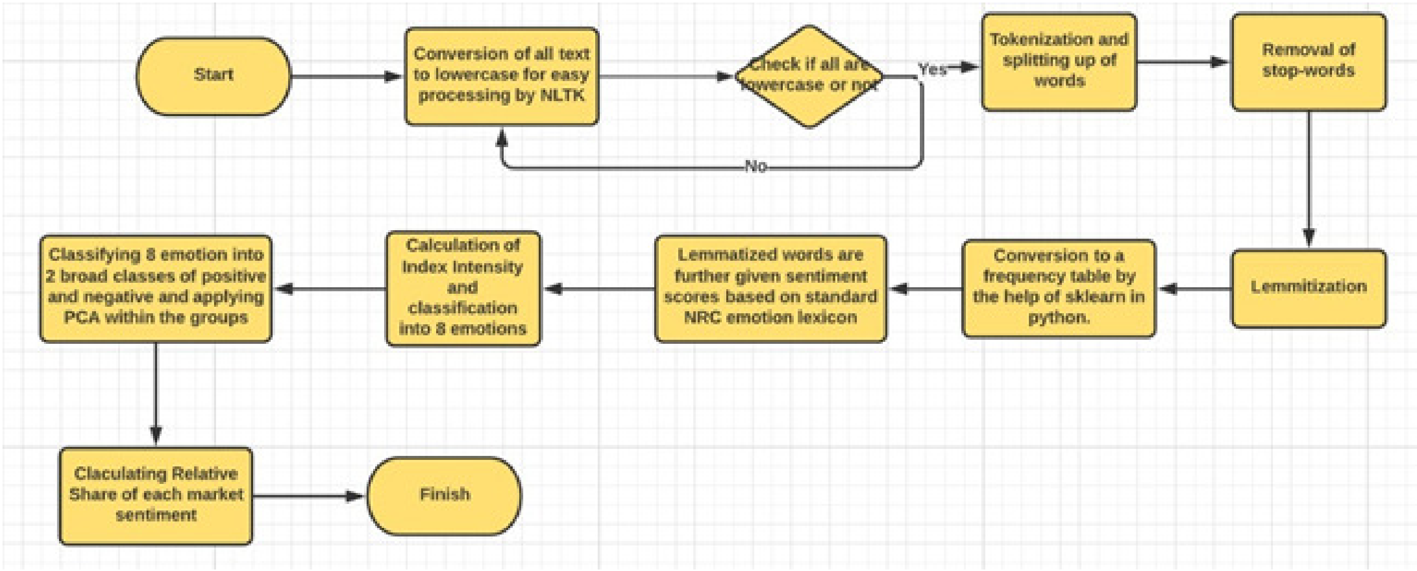

Start
Conversion of all text to lowercase for easy processing by NLTK
Check if all are lowercase or not
Yes
No
Tokenization and splitting up of words
Removal of stop-words
Lemmitization
Conversion to a frequency table by the help of sklearn in python.
Lemmatized words are further given sentiment scores based on standard NRC emotion lexicon
Calculation of Index Intensity and classification into 8 emotions
Classifying 8 emotion into 2 broad classes of positive and negative and applying PCA within the groups
Claculating Relative Share of each market sentiment
Finish

Fig 3.6 Methodology used in paper 'Sentiment Analysis of Indian Stock Market Volatility'

c) Advantages

When we analyse the finding it is very much clearly evident that the noise traders play a dominant role. An advantage of finding a real stream of data is that it is more useful in daily life. This stream of data is found to be more dynamic in nature than traditional monthly and quarterly indicators. Also, the given model does not consider positive and negative errors in the mean equation and instead of that the model has generated separate market sentiments on conditional volatility of the Indian financial market. This approach is better and more appealing in today's financial market.

d) Disadvantages

The first disadvantage of the proposed work is that only 8 emotions are used in which they are divided into 2 classes only. The number of emotions should be increased; another broader class known as neutral can be added in order to analyse the sentiment. Future scope of this study lies in a comparative analysis of different sectors of the Indian stock market like energy, telecommunication or metal.

3.7 Estimating the relative effects of raw material prices, sectoral outlook and market sentiment on stock prices [7]

a) Aim
To determine the effect of raw material prices in different time periods, outlook of different sectors in the market and market sentiment on the share prices of the company. The problem addressed is also to ascertain the relative strength of the above mentioned factors depending on the time period. Important internal factor which affects the companies performance and stock prices is raw materials, the main aim is to understand the relation between stock prices and prices of the raw material of a particular company.

b) Methodology and Result
The particular paper resorts to wavelet analysis and machine learning models to predict the relation between. Wavelet coherence and correlation analysis have been done to determine relation between raw material, sector outlook and market sentiment over a set of Indian companies for a short, medium and long period of time. Certain machine learning algorithms like Random forest, gradient boosting and genetic algorithms have also been used to determine the rank of the three factors mentioned above over different time periods.
The algorithms used in the particular paper were :
Random Forest : It is a machine learning algorithm used to solve regression and classification problems.
Gradient Boosting : It is based on the Greedy algorithm and can overfit a dataset quickly. It penalises various parts of the algorithm and improves the performance by reducing overfitting.
Genetic Algorithm : It is a method for solving constrained and unconstrained optimization problems which are based on the natural selection process.

Formula used :

1. CWT of a time series

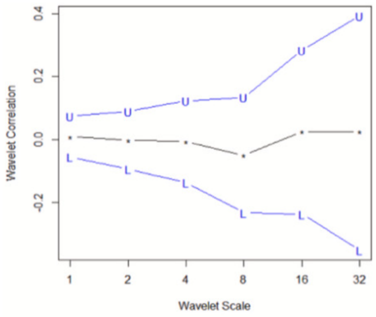
$$W_{x}(\Gamma, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{+\infty} x(t) \psi^{*} \left(\frac{t-\Gamma}{s}\right) dt$$

Description: Continuous wavelet transform based coherence analysis

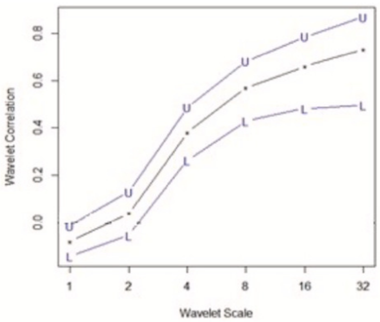
2. MODWT estimator of wavelet correlation

$$\rho_{xy}(\lambda_j) = Corr\,(w_{ijt}, \overline{w}_{ijt}) = \frac{Cov(w_{ijt}, \overline{w}_{ijt})}{\sqrt{Var(w_{ijt})Var(\overline{w}_{ijt})}}$$

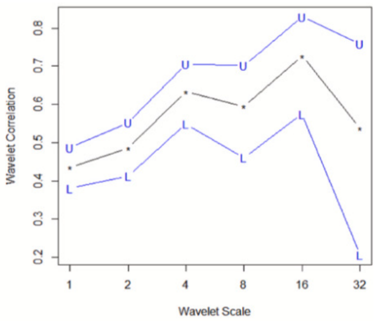
Description: The MODWT estimator of wavelet correlation has been used in this study which basically considers the covariance of two series (x(t), y(t)) and wavelet variance of individual series



Reliance Stock Price and Crude Oil Price



Reliance Stock Price and Oil & Gas Index



Reliance Stock Price and SENSEX

A related problem was found in another paper also. It is stated that different sectors in an economy behave differently depending upon their trend pattern, characteristic of the sector and also some uncertainties that lead to randomness. The objective is to find out for certain sectoral characteristics of the stock market over different time periods **[33].** A similar trend of comparing Indian companies was also seen in another paper. The objective was to assess the innovation of Indian companies and to analyse the changes due to these innovations. Three types of innovations are taken into consideration : Product, marketing and process innovation. It also assesses the strategies formulation by these companies **[34].** Regarding consideration of different time periods, one of the research papers analysed the change in value of Bitcoin returns, change in Gold price returns, US Stock Market returns, interest rates, crude oil and rapid change in American Stock Market. To make the outcomes more robust , two different time periods have been taken into consideration **[35]**.

c) Advantages

1. One of the main advantage of wavelet is that they offer a simultaneous localisation in time and frequency domain
2. The use of larger DWT basis functions or wavelets filters produces blurring and ringing noise near edge regions in images or video frames
3. The second main advantage of wavelets is that, using a fast wavelet transform, it is computationally very fast.
4. Provide a way for analysing web forms in both frequency and duration.
5. Representation of functions that have discontinuities and sharp pics.
6. Accurately deconstructing and reconstructing finite, non-periodic and non-stationary signals.
7. Allow signals to be stored more efficiently than by Fourier transform.

d) Disadvantages

1. A poor directional selectivity for diagonal features, because the wavelet filters are separable and real.
2. Longer compression time.
3. And lack of shift invariance, in which means that small shifts in the input signal can cause major variations in the distribution of energy between DWT coefficients at different scales.
4. The cost of computing DWT as compared to DCT may be higher.

3.8 Exploiting textual and relationship information for fine-grained financial sentiment analysis [8]

a) Aim

Identification of expressions (positive neutral negative) towards the subject by way of expressing sentiments in text. Novel approach to capture implicit sentiments and the contagion process.

In a financial firm, sentiment could be read across platforms like company, analyst reports, news articles and blogs. The aim is to capture implicit sentiments and the contagion process. To apply the solution of sentiment analysis across multiple domains and text types, such as product reviews. And to demonstrate the impact of implicit sentiment as well as importance of different relationship or sentiment prediction on company and analyst reports, news articles and blogs.

b) Methodology and Result

Proposed approach as per given in the paper includes text and graph FFNN (feed forward neural network) or a Fine Tuned Textual Representation FFNN (feed forward neural network).

The paper uses aFFNN for its calculations, FFNN is based on LMBP algorithm , LMBP uses all the sample information to modify the weight and threshold and it can adjust or modify weight and threshold of the model.

The improvement from baseline was seen from 0.68 - 15.1% and 59.46–234.15% for the CS and MSE, respectively.

A comparison of fine tuned BERT and fine tuned FFNN , showed that FFNN outperforms fine tuned BERT. Fine tuned FFNN had the best performance as compared to the other two models.

Equation used :

1. Mean Squared Error (MSE)

$$MSE(P, T) = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(T_i - P_i)^2}$$

Description: mean square error measures the average of the squares of the error.

2. Cosine Similarity(CS)

$$CS(T, P) = \frac{\sum_{i=1}^{n} T_i * P_i}{\sqrt{\sum_{i=1}^{n} T_i^2} * \sqrt{\sum_{i=1}^{n} P_i^2}}$$

Description : cosine similarity is the cosine of the angle between two N-dimensional vectors in an N-dimensional space.

One of the papers used the following datasets to meet their objectives : IMDB corpus, Sentiment stanford sentiment treebank, Sentiment140, SemEval2017 Task 4, SemEval2017 Task 5, The SSIX Corpora, FiQA 2018 Challenge, [36]. The objective of this paper is to form a novel corpus which contains various reports, Company reports, articles from the newspaper and micro-blogs from StockTwits and to analyse the entire corpus in order to determine the sentiment of a company. To foster on the financial sentiment analysis and potential application in behavioural science **[36]**. Another paper resorted to content of news articles to form a relation between reaction of the market and news articles **[37]**. One of the papers worked with graphs and processed graphs of different kinds like directed, and directed, labelled and cycling graphs **[38]**. On a similar basis, one paper worked on finding a way to represent and encode graph structure so that it can be easily used by machine learning models. Currently machine learning models rely on user defined heuristics to extract the different features and encode structural information **[42]**.

c) Advantages

1. Problems in FFNN are represented by attribute-value pairs.
2. These learning methods are quite robust to noise in the training data. The training examples may contain errors, which do not affect the final output.
3. It is used where the fast evaluation of the learned target function is required.

d) Disadvantages

1. It is highly dependent on hardware.
2. Lack of assurance of proper network structure.
3. The difficulty to show the problem to the network.

3.9 Harvesting social media sentiment analysis to enhance stock market prediction using deep learning [9]

a) Aim

To identify how movements in a company's stock prices correlate with expressed opinions of the public regarding that company. And to make a stock price prediction tool which considers public sentiment and also other parameters. Data will be gathered from social networking sites like Twitter, Facebook, Google plus etc. Social networking sites perfectly reflect People's opinion on a particular company or a particular news. It is found from a survey that financial news has an impact on stock prices of a particular company.

b) Methodology and Result

Using Deep Learning Model and LSTM(Long short term memory) a reliable predictive model for stock movement is built. LSTM is a form of RNN and is likely to learn long-term dependencies. LSTM allows RNN to keep track of their input data over a long time.Stock Values of companies were taken from NSE stock data, Sentiment value was used as a metric to compare. Sentiment value lies between -1 and +1 , and depending on this value the different companies stock value can be determined whether it will increase or decrease.

The average sentiment estimates the regular sentiment of any topic over a given period. The experiments done considered opinions, primary sentiment, precision and recall. Stock prediction using different social media platforms resulted in more accuracy and reliability than previous predictions that were made.

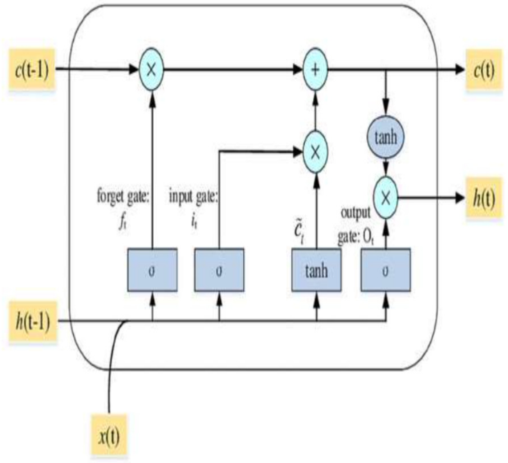


Fig. LSTM Model with its three layer

Similar Machine learning models and deep learning models were also used in order to predict stock value of a company over a long period of time using machine learning models **[39]**. LSTM was also used to develop an innovative neural network approach to achieve better stock market predictions. To propose the deep long short term memory neural network LSTM with embedded layer and long short term memory neural network to predict the stock market **[40]**. Making use of user generated blogs is also a good method to predict the stock prices **[41]**. This is a potential use of textual information.

c) Advantages

1. LSTM provides various parameters like learning rates, and input and output biases.
2. There is no need for fine adjustments.
3. Complexity is reduced to O(1) with LSTM.

d) Disadvantages

1. LSTMs get influenced by various irregular weight introductions and consequently act very like that of a feed-forward neural net. They incline toward little weight introducing all things being equal.

2. LSTMs are inclined to overfitting and it is hard to apply the dropout calculation to check this issue. Dropout is a regularisation technique where input and intermittent associations with LSTM units are probabilistically avoided from initiation and weight refreshes while preparing an organisation.

3.10 Market sentiment-aware deep reinforcement learning approach for stock portfolio allocation [10]

a) Aim
To solve stock portfolio allocation and maintain it to get maximum return with minimum risk involved.

b) Methodology and Results
An adaptive, sentiment-aware deep deterministic policy gradient is used to solve portfolio allocation that not only learns from historical stock price trends, but also from market sentiment – which is an influential environment input that captures the overall mood of investors. They've consolidated an extensive dataset of Google News and Twitter tweets that reflect the sentiment of the 30 Dow Jones companies. It also provided the methodology and mathematical definitions used to calculate market sentiment, and enabled the adaptive DDPG algorithm to leverage it sufficiently. Other papers used different approaches to solve the financial problem of portfolio selection. One of the papers created a situation of winners and losers in selection of stock microblogs using sentiment analysis **[43]**. Deep learning is also used in some cases for forecasting the stock returns in different stock markets like the Japanese stock market etc and the performance of methods is investigated **[44].**Other papers in the same domain found an appropriate modelling system that can incorporate the complexities of the stock market and generate practical trading strategies**[45].** So, most of the papers in this domain were investigating the role of market sentiment in an asset allocation problem and thus the main conclusion was to come up with Dynamic portfolio optimization, process of sequentially allocating wealth to a collection of assets in some consecutive trading periods, based on investors' return-risk profile but automating this process with machine learning remains a challenging problem**[46].**

News Sentiment Score $$\mathbf{NS}_{(\mathbf{c},\mathbf{d})} = \frac{\sum_{i=1}^{N} PS(a(i,c,d))}{N}$$

Twitter Sentiment Score $$\mathbf{TS}_{(\mathbf{c},\mathbf{d})} = \frac{\sum_{i=1}^{N} TS(t_{(i,c,d)})PS(t_{(i,c,d)})}{N}$$

Confidence Score $$\mathbf{CS}_{(\mathbf{c},\mathbf{d})} = \frac{NS(c,d) + TS(c,d)}{2}$$

It is noteworthy that the sentiment aware approach has significant improvements across all the considered metrics compared to the baselines. With an initial investment of 10,000 dollars, the final portfolio value of our approach reaches 25,051 dollars which is much higher than 21,881 dollars by Adaptive DDPG and 18,156 dollars by DDPG. This approach achieves an annualized rate of return of 22.05% as compared to 18.85% and 14.7% returns by Adaptive and DDPG respectively. The risk taken by this model is also lesser compared to the other baselines as shown by obtaining the least annualized standard deviation error of 0.096. With a 2.07 Sharpe ratio value, our sentiment-aware approach is shown to be more robust and effective in balancing return and risk compared to 1.49, 0.93 for the adaptive DDPG and DDPG respectively.

c) Advantages
Deep Deterministic Policy Gradient (DDPG) is a model-free off-policy algorithm for learning continuous actions. It combines ideas from DPG (Deterministic Policy Gradient) and DQN (Deep Q-Network). It uses Experience Replay and slow-learning target networks from DQN, and it is based on DPG, which can operate over continuous action spaces.

d) Disadvantages

In environments with continuous state and action spaces, Deep Deterministic Policy Gradient (DDPG) algorithms can solve very complex problems, yet can also fail in environments that seem trivial, but the reason for such failures is still poorly understood.

3.11 Stock Prediction by using NLP and Deep Learning Approach [11]

a) Aim
To properly recognize which shares to promote with a purpose to get more profits.

b) Methodology and Results

System is developed with Natural Language Processing (NLP) techniques of computer science and Convolutional Neural Network (CNN) of Deep Learning. Natural Language Processing technology is used to facilitate a system to search out companies with excellent news in terms of live performance in the market. That helped to facilitate the selection of the best performers in the market. NLP is used to classify news in positive and negative sets and to provide a performance graph of selected organizations. We got to know the best performing company. Natural Language Processing provides a system NLP (Natural Language Processing) that works on our twits for detecting merchandise and its impact. The other related papers utilized a single system to determine the stock market's opening value. However, their built system was self-learner, allowing them to estimate the market's opening value. They had fed the stock data into their custom-built algorithm, which calculated the anticipated value**[48].** Some papers also tried the ANN algorithm approach to predict the stock market prices and also discovered proper findings**[49]**.

CNN has the characteristic of paying attention to the most obvious features in the line of sight, so it is widely used in feature engineering. With comparison to other approach i.e., ANN algorithm CNN performs much better.The proposed CNN achieved relatively higher prediction accuracy of 84.6%, while the ANN, SVM, and KNN algorithms obtained prediction accuracies of 73.5%, 67.9%, and 65.9% using 11 HRV features, respectively. Other papers employed a sentiment analysis technique for stock tweets that were related to a different type of products and so extracted stock related tweets from various social networking sources. To determine the polarity of tweets, they applied the SVM approach**[47]**.

c) Advantages

A CNN with a fully connected network learns an appropriate kernel and the filtered image is less template-based. A fully-connected network with 1 hidden layer shows lesser signs of being template-based than a CNN.CNN has the characteristic of paying attention to the most obvious features in the line of sight, so it is widely used in feature engineering. With comparison to other approaches i.e., ANN algorithm CNN performs much better for stock price prediction.

d) Disadvantages

CNN does not encode the position and orientation of objects. Lack of ability to be spatially invariant to the input data. Lots of training data is required. If CNN-LSTM was used it can provide reliable stock price forecasting with the highest prediction accuracy.

3.12 An Efficient Word Embedding and Deep Learning Based Model to Forecast the Direction of Stock Exchange Market Using Twitter and Financial News Sites: A Case of Istanbul Stock Exchange (BIST 100) [12]

a) Aim
Prediction of stock price in Istanbul Stock Exchange

b) Methodology and Results

To forecast the direction of stocks is significant for investors, analysts, and researchers. In this study, we propose to predict the direction of stocks in the Turkish stock market (BIST100) by employing Turkish texts such as social media platforms. For this purpose, different deep learning methodologies**[51]**. Long short-term memory networks, recurrent neural networks, convolutional neural networks as deep learning algorithms and Word2Vec, GloVe, and FastText as word embedding models are evaluated. To demonstrate the effectiveness of the proposed model, four different sources of Turkish news are collected. The news articles about stocks from Public Disclosure Platform (KAP), text-based technical analysis of each stock from Bigpara, user comments from both Twitter and Mynet Finans platforms are gathered.

The stock market parameter forecasting is an important research subject both for financial professionals and the machine learning experts due to the challenges and opportunities it possesses. Despite the difficulties in financial data, interest in this research area is growing rapidly**[50]**.So, to estimate the direction of Borsa Istanbul 100 Index by using financial sentiment analysis and to enrich the datasets with various techniques from a semantic perspective and improve the classification performance of system by blending ensemble learning approach with deep learning algorithms**[51]**.

c) Advantages

The main Advantage is that since the model uses RNN, LSTM, Machine Learning and Deep Learning models the prediction of stock prices will be more accurate. And also, in the model it can predict the future 30 days Stock Prices and it can show it in a graph. Also, the main feature is that the model can show an output of the Individual Predicted Close prices of the Predicted 30 days.

d) Disadvantages

LSTM require 4 linear layer (MLP layer) per cell to run at and for each sequence time-step. Linear layers require large amounts of memory bandwidth to be computed, in fact they cannot use many computes unit often because the system has not enough memory bandwidth to feed the computational units.

4. EVALUATION METHODS AND DATASETS

4.1 Evaluation methods and metrics used

F1 Score Precision and Recall are complementary metrics that have an inverse relationship. If both are of interest to us then we'd use the F1 score to combine precision and recall into a single metric.

Mean Reciprocal Rank (MRR) The Mean Reciprocal Rank (MRR) evaluates the responses retrieved, in correspondence to a query, given their probability of correctness. This evaluation metric is typically used in informational retrieval tasks quite often.

Mean Average Precision (MAP) Similar to MRR, the Mean Average Precision (MAP) calculates the mean precision across each retrieved result. It's also used heavily in information retrieval tasks for ranked retrieval results.

Root Mean Squared Error (RMSE) When the predicted outcome is a real value then we use the RMSE. This is typically used in conjunction with MAPE — which we will cover next — in the case of regression problems, from tasks such as temperature prediction to stock market price prediction.

Mean Absolute Percentage Error (MAPE) The MAPE is the average absolute percentage error for each data point when the predicted outcome is continuous. Therefore, we use it to test evaluate the performance of a regression model.

Area Under the Curve (AUC) The AUC helps us quantify our model's ability to separate the classes by capturing the count of positive predictions which are correct against the count of positive predictions that are incorrect at different thresholds.

Metrics used in our problem domain are:

- Mean Squared error (avg - 0.0693)
- Cosine Similarity (avg - 0.79945)
- Sentiment Value (positive sentiment value 0.01355 , negative sentiment value -0.0063)
- Sharpe Ratio
- Annualized return comparisons
- Annualized standard errors
- Final portfolio value vs predicted value

4.2 Popular datasets used

- BSE(Bombay stock exchange) and NSE(National Stock Exchange) websites - all the information related to the stock prices of the companies have been taken from bse and nse websites, which are the best resources for such data as they update it regularly and are the most reliable sources for stock prices.
- IMDB dataset & Yelp dataset - Yelp Data set contains information about eight metropolitan areas in the USA and Canada. IMDB data set contains data over 25,000 reviews labelled according to the sentiment (Positive or negative).
- News from Money control, Google News and Economic Times - News sites like money control, Economic Times, IFL are trusted sources and they have enough information about stock related stuff.. Twitter is the one of largest social media to house tweets related to stock market and share prices of numerous companies.

- Twitter and other social media platforms - Here customers share their genuine opinion about the product and using those as the input can be really helpful in detecting the stock and portfolio future prices.
- NASDAQ Stock Price and TOPIX500 Stock Price.
- Stock-related financial data are from the CSMAR database

5. COMPARISON OF BASE PAPERS

Title	Scope of work	Existing algorithms used	Datasets used	Evaluation metrics and corresponding performance gains	Limitations faced
Prediction of stock values changes using sentiment analysis of stock news headlines **[1]**	To analyse stock value changes and predictions of the stock values using fresh scraped economic news about the companies	RNN, NLTK Vader Lexicon, Text Blob	IMDB review dataset	NLTK Vader lexicon , Text blob, RNN	Disadvantage is the whole system depends on news headlines and user response. Due to this we need user response in-order to habitat with this method. If time arise when we have no news headline based on stock prises which might cause failure of this service. But the above mentioned problem have 10^-9%* chances of happening.
A Method of Using News Sentiment for Stock Investment Strategy **[2]**	This study evaluates the sentiment of Japanese news and attempts to apply it to investment strategies in individual stocks.	LSTM, RNN	TOPIX500 Stock Prices	Equal weighted, Market Value weighted of cumulative excess return of daily rebalance energy	The disadvantage is making news headlines in order to maintain the share market is against human faith. Not only this, by this way any government body can easily manipulate future results.

Augmented Textual Features-Based Stock Market Prediction **[3]**	To predict stock market, due to its dynamics, non-linearity and complexity nature	DNN, Deep CNN, LSTM	NASDAQ Stock Price	Dickey-fuller test to check stationarity. Machine learning techniques. Granger causality test for the four stocks. Tweet mining	The demerit is still there are chances that data might get false in some exceptional case when false reviews are done.
The Impact of COVID-19 on the Chinese Stock Market: Sentimental or Substantial? **[4]**	In this paper the authors have investigated the impact on the Chinese Stock Market caused by COVID-19 by doing an event study and examining the effect of individual investor sentiment on their returns.	Panel regression model, Fama French model	Stock-related financial data are from the CSMAR database, Sentiment data used in this work is GubaSenti	Share market daily return, sample stock daily return	This paper is mainly focussed on 7 industries so this cannot be used as a basis for other industries.
Detecting a Risk Signal in Stock Investment Through Opinion Mining and Graph-Based Semi-Supervised Learning **[5]**	To avoid credit events that might cause a national and global economic crisis ultimately leading to socioeconomic losses	Logistic regression model Linguistic rule-based model graph-based semi-supervised learning	Data related to Hyundai Merchant Marine	(1) data collection and filtering, (2) credit risk assessment and early signal detection, and (3) prediction of credit events.	Despite the fact that each company is required to provide information about its financial health and significant changes in operations and management, some companies may conceal their unfavourable position. As a result, certain events are not visible or are concealed, making it harder to discover these hidden occurrences, which might result in a significant loss.
Sentiment Analysis of Indian Stock Market Volatility **[6]**	This paper attempts to shape the volatility of Indian Stock market using investor	Natural Language Toolkit(NLTK) and Principal Component Analysis(PCA), Sklearn feature	The datasets that are used in the above study are the prominent web sources for the Indian financial market and	GARCH model	The first disadvantage of the proposed work is that only 8 emotions are used in which they are divided into 2 classes only. The number of emotions should be increased another broader class known as neutral can be

		extractor	business.		added in order to analyse the sentiment. Future scope of this study lies in a comparative analysis of different sectors of Indian stock market like energy, telecommunication or metal.
Estimating the relative effects of raw material prices, sectoral outlook and market sentiment on stock prices **[7]**	To determine the relation between movement of raw material prices and share price of the company. The scope of the problem is limited to the following sectors : Oil and Gas, Metal, FMCG and Healthcare.	Random Forest, Gradient Boosting, Genetic Algorithm	BSE(Bombay stock exchange) and NSE(National Stock Exchange) websites	Boruta Algorithm Random Forest Gradient Boosting Genetic Algorithm Monto Carlo Methods for deriving significance.	A poor directional selectivity for diagonal features, because the wavelet filters are separable and real. Longer compression time. And lack of shift invariance, in which means that small shifts in the input signal can cause major variations in the distribution of energy between DWT coefficients at different scales. The cost of computing DWT as compared to DCT may be higher.
Exploiting textual and relationship information for fine grained financial sentiment analysis **[8]**	Identification of expressions (positive neutral negative) towards the subject by way of expressing sentiments in text. Novel approach to capture implicit sentiments and the contagion process.	aFFNN, LMBP algorithm.	IMDB dataset and Yelp dataset	Mean squared error (MSE) , Cosine Similarity (CS)	1. It is highly dependent on hardware. 2. Lack of assurance of proper network structure. 3. The difficulty to show the problem to the network.

Harvesting social media sentiment analysis to enhance stock market prediction using deep learning **[9]**	To identify how movements in a company's stock prices correlate with expressed opinions of the public regarding that company.	RNN algorithm, LSTM algorithm.	Money Control, IFL, Economic Times, Twitter, NSE Stock Data	Sentiment value was used as a metric to compare.	LSTMs get influenced by various irregular weight introductions and consequently act very like that of a feed-forward neural net. They incline toward little weight introducing all things being equal. LSTMs are inclined to overfitting and it is hard to apply the dropout calculation to check this issue. Dropout is a regularisation technique where input and intermittent associations with LSTM units are probabilistically avoided from initiation and weight refreshes while preparing an organisation.
Market sentiment-aware deep reinforcement learning approach for stock portfolio allocation **[10]**	To solve stock portfolio allocation and maintain it to get maximum return with minimum risk involved.	DPG and DDPG	Google News, Twitter	Sharpe Ratio Annualized Return Annualized Std. Error Final Portfolio Value	In environments with continuous state and action spaces, Deep Deterministic Policy Gradient (DDPG) algorithms can solve very complex problems, yet can also fail in environments that seem trivial, but the reason for such failures is still poorly understood.
Stock Prediction by using NLP and Deep Learning Approach **[11]**	To properly recognize which shares to promote with a purpose to get more profits.	CNN	Twitter Tweets, top 5 performing companies' data in IT sector	Market Value Comparison	CNN does not encode the position and orientation of objects. Lack of ability to be spatially invariant to the input data. Lots of training data is required. If CNN-LSTM was used it can provide a reliable stock price forecasting with the highest prediction accuracy
An Efficient	Prediction of stock	CNN, RNN,	Twitter, KAP,	F-criterion and accuracy	LSTM require 4 linear

Word Embedding and Deep Learning Based Model to Forecast the Direction of Stock Exchange Market Using Twitter and Financial News Sites: A Case of Istanbul Stock Exchange (BIST 100) **[12]**	price in Istanbul Stock Exchange	Word embedding models	Mynet Finans, Bigpara		layer (MLP layer) per cell to run at and for each sequence time-step. Linear layers require large amounts of memory bandwidth to be computed, in fact they cannot use many computes unit often because the system has not enough memory bandwidth to feed the computational units.

6. Conclusion and future work

With this paper our motive was to generalise and represent various recent trends happening in the stock market with respect to sentiment analysis. The papers discussed above give a wide prospect about various techniques which can be used to predict the market. Along with prediction the papers present some alerts which must be taken care of when handling Sentimental analysis in stock prediction.

In the first paper the authors analysed the difference of emotional graph and trading graph correlation. They applied various techniques and made a set of results. In which some techniques were giving high opening and closing differences as well as minor differences in highest and lowest value of a stock price. Along with this they came to a conclusion that Economic news has an impact on the stock market irrespective of its textual context. They even concluded that there is no neutral emotion, since every emotion caused an impact on the market **[1]**.

In the second paper the focus was made to find the prediction duration and its life expectancy. On doing various experiments it was found that the sentimental analysis prediction is really short lived. The impact caused on stock price due to a certain sentimental headline is really short living. None of the sentimental predictions can predict stock for a week or month. Thus for people who are doing day to day trading for them sentimental analysis is the best technique **[2]**.

Not only this if a certain headline is on the front page or the first bullet news then the impact caused on that stock is high as compared to headlines on the next page. It was even found that articles with more texts can cause major impact as compared to articles with less words **[2]**.

In the third paper it is observed that the sentimental prediction provided a regular pattern. This regular pattern can be really helpful for intra day trading. Since as discussed before sentimental prediction world for a day or two. Thus getting such a regular pattern can be helpful in such a short duration. But along with the derivation and usage of regular patterns one should always remember there is a high chance of getting that pattern to mislead a prediction. Because being in such a volatile market where linearity is near to nil we can totally depend on a pattern and trade. Thus such patterns must only be accepted if found true for a large amount of data **[3]**.

In the forth paper, it is observed that pandemics can generate widespread negative sentiment, resulting in investor concern and market volatility. Stock return volatility during the epidemic is influenced by sentiment and is not just due to economic losses.Due to the high unpredictability of epidemics, investors could get excess return by holding bellwether stocks of the pharmaceutical industry in the first stage. Then, investors should gradually reduce stockholdings in the pharmaceutical industry and increase stockholdings highlighted by the government. In addition, stocks with high risk factors, such as high P/E and P/B ratios, high CMV, low institutional shareholding ratio, and low net assets, should be avoided during the middle and late stages of the epidemic **[4]**. The future scope of this is to the UN's food crisis alarm, the food business has become a new emphasis in the post-event window. As a result, it's worth looking into the function of industry influences in epidemics.

In the fifth paper, they have suggested a new algorithm to support decision-making in stock investment by detecting early signals and predicting the occurrence probability of credit events through opinion mining and logistic regression models**[5]**. A major objective of this paper is to detect risk in the stock market using sentiment analysis, if one becomes aware of risk he/she is able to be prepared and change their course of action. They have made use of filtering fake information, assessing credit risk and detecting risk signals and predicting future occurrences of credit events through sentiment analysis, word2vec, and graph-based semi-supervised learning which have a large scope for different future work in real world problems.

In the sixth paper, their main focus is to oppose the point made by Markovits which states that the rational behaviour of investors and market fundamentals is believed to be the sole factor that plays a decisive role in shaping the decision of such investors**[30].** This paper departs from the traditional approach of modeling conditional volatility using standard macroeconomic or financial indicators as sentiment factors to gauge their impact on conditional volatility of the market. We employed a novel approach of using news driven sentiment analysis and further augment the volatility models with such sentiment factors to measure different types of sentiments in the Indian market. Major findings of the paper suggest the dominant role of negative sentiments in shaping conditional volatility in the Indian stock market. Findings also support evidence of noise traders which signifies immaturity of the Indian financial market. **[6].**

In the seventh paper, the present scope of the paper is limited to market sectors namely : Oil and Gas, Metal, FMCG and Healthcare. By the proposed frameworks the study can include different sectors of the market too in the future. The paper contributes to relevant literature by combining or uniting wavelet analysis and machine learning to determine the relation between the movement of raw materials and share prices of a company, which affects the end consumer. The scope of the problem is limited to the following sectors : Oil and Gas, Metal, FMCG and Healthcare. The suggested methods and frameworks mentioned in the paper can be used to determine the required relation for other sectors as well **[7]**.

In the eighth paper, Future scope of this paper includes exploring dynamic vertices like GraphSAGE. This will reduce re-calculation of vertex representation for the entire graph. Different classifiers can be used to further optimise the performance.
The particular paper mainly focuses on showcasing the textual context that can be modelled on lithography, to study and gain further insight into sentiment analysis and improve it **[8]**.

In the ninth paper, the use of news articles, social media like Twitter, Facebook explains how a company performs in the share market. This will help the common user to predict the stock market and invest wisely and get a good return in the long term. We can get stock accuracy so that the user can buy or sell stock of a particular company. There are future opportunities for research in this area. The method can be made more accurate and more optimised in the future by making some changes or using a different algorithm **[9]**.

In the tenth paper future work could focus on acquiring more tweets per day, expanding acquisition to get insights from different sources such as stock market-specific news websites (CNBC, Business Standard, etc.), and processing photos, as most tweets and news online are now provided as image snippets. For this case, multi-agent reinforcement learning algorithms can be investigated. Presence of several exogenous restraints on retail and institutional traders, such as transaction fees, trading restrictions, cash holding restrictions, and liquidity shortages will be checked. Furthermore, due to the extensive use of metaphors, sarcasm, domain specific terminology, and other indirect linguistic references in common language, especially in material that expresses an opinion, natural language processing on financial data is a non-trivial effort. Being able to grasp such language might aid in more accurately predicting market sentiment**[10]**.

In the eleventh paper the future work could focus on executing more calculations and all the newer methods planning to give live proposals to securities exchange financial specialists. Additionally, their emphasis will be on the entire securities exchange for forecasting**[11]** and also authors tried to increase the data set and also tune the parameters to predict more accurate value of stock prices**[12]**.

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References

[1] Nemes, L., & Kiss, A. (2021). Prediction of stock values changes using sentiment analysis of stock news headlines. Journal of Information and Telecommunication, 1-20.

[2] Katayama, D., & Tsuda, K. (2020). A Method of Using News Sentiment for Stock Investment Strategy. Procedia Computer Science, 176, 1971-1980.

[3] Bouktif, S., Fiaz, A., & Awad, M. (2020). Augmented textual features-based stock market prediction. IEEE Access, 8, 40269-40282.

[4] Sun, Y., Wu, M., Zeng, X., & Peng, Z. (2021). The impact of COVID-19 on the Chinese stock market: Sentimental or substantial? Finance Research Letters, 38, 101838.

[5] Yoon, B., Jeong, Y., & Kim, S. (2020). Detecting a Risk Signal in Stock Investment Through Opinion Mining and Graph-Based Semi-Supervised Learning. IEEE Access, 8, 161943-161957.

[6] Paramanik, R. N., & Singhal, V. (2020). Sentiment Analysis of Indian Stock Market Volatility. Procedia Computer Science, 176, 330-338.

[7] Ghosh, I., Chaudhuri, T. D., Alfaro-Cortés, E., Martínez, M. G., & Rubio, N. G. (2021). Estimating the relative effects of raw material prices, sectoral outlook and market sentiment on stock prices. Resources Policy, 73, 102158.

[8] Daudert, T. (2021). Exploiting textual and relationship information for fine-grained financial sentiment analysis. Knowledge-Based Systems, 107389.

[9] Mehta, P., Pandya, S., & Kotecha, K. (2021). Harvesting social media sentiment analysis to enhance stock market prediction using deep learning. PeerJ Computer Science, 7, e476.

[10] Koratamaddi, P., Wadhwani, K., Gupta, M., & Sanjeevi, S. G. (2021). Market sentiment-aware deep reinforcement learning approach for stock portfolio allocation. Engineering Science and Technology, an International Journal, 24(4), 848-859.

[11] Deshmukh, R. (2021). Stock Prediction by using NLP and Deep Learning Approach. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 12(1S), 202-211.

[12] Kilimci, Z. H., & Duvar, R. (2020). An Efficient Word Embedding and Deep Learning Based Model to Forecast the Direction of Stock Exchange Market Using Twitter and Financial News Sites: A Case of Istanbul Stock Exchange (BIST 100). IEEE Access, 8, 188186-188198.

[13] K. Ravi and V. Ravi, "A survey on opinion mining and sentiment anal- ysis: Tasks, approaches and applications," Knowl.-Based Syst., vol. 89, pp. 14–46, Nov. 2015.

[14] J. Bollen, H. Mao, and A. Pepe, "Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena," in Proc. 5th Int. AAAI Conf. Weblogs Social Media, 2011, pp. 450–453.

[15] T. Sun, J. Wang, P. Zhang, Y. Cao, B. Liu, and D. Wang, "Predicting stock price returns using microblog sentiment for chinese stock market," in Proc. 3rd Int. Conf. Big Data Comput. Commun. (BIGCOM), Aug. 2017, pp. 87–96.

[16] K.IchinoseandK.Shimada,"Stockmarketpredictionfromnewsonthe Web and a new evaluation approach in trading," in Proc. 5th IIAI Int. Congr. Adv. Appl. Informat. (IIAI-AAI), Jul. 2016, pp. 78–81.

[17] V.S.Pagolu,K.N.Reddy,G.Panda,andB.Majhi,"Sentiment analysis of Twitter data for predicting stock market movements," in Proc. Int. Conf. Signal Process., Commun., Power Embedded Syst. (SCOPES), Oct. 2016, pp. 1345–1350.

[18] D. Lv, S. Yuan, M. Li, and Y. Xiang, "An empirical study of machine learning algorithms for stock daily trading strategy," Math. Problems Eng., vol. 2019, Apr. 2019, Art. no. 7816154.

[19] Daisuke Katayama and Kazuhiko Tsuda. (2018) "A Method of Measurement of The Impact of Japanese News on Stock Market." 22nd International Conference on Knowledge-Based and Intelligent Information & Engineering Systems KES2018

[20] S. Bouktif and M. Adel Awad, "Predicting stock market movement: An evolutionary approach," in Proc. 7th Int. Joint Conf. Knowl. Discovery, Knowl. Eng. Knowl. Manage., 2015, pp. 159–167.

[21] D.Shah,H.Isah,andF.Zulkernine,"Predictingtheeffectsofnewssenti- ments on the stock market," in Proc. IEEE Int. Conf. Big Data, Dec. 2018, pp. 4705–4708.

[22] A.Picasso,S.Merello,Y.Ma,L.Oneto,andE.Cambria,"Technicalanal- ysis and sentiment embeddings for market trend prediction," Expert Syst. Appl., vol. 135, pp. 60–70, Nov. 2019.

[23] P. D. Yoo, M. H. Kim, and T. Jan, "Machine learning techniques and use of event information for stock market prediction: A survey and evaluation," in Proc. IEEE Int. Conf. Comput. Intell. Modelling, Control Automat., Int. Conf. Intell. Agents, Web Technol. Internet Commerce,

vol. 2, Nov. 2005, pp. 835–841.

[24]Al-Awadhi, A. M., Alsaifi, K., Al-Awadhi, A., & Alhammadi, S. (2020). Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. Journal of behavioral and experimental finance, 27, 100326.

[25] Liu, H., Manzoor, A., Wang, C., Zhang, L., & Manzoor, Z. (2020). The COVID-19 outbreak and affected countries stock markets response. International Journal of Environmental Research and Public Health, 17(8), 2800.

[26]Baig, A. S., Butt, H. A., Haroon, O., & Rizvi, S. A. R. (2021). Deaths, panic, lockdowns and US equity markets: The case of COVID-19 pandemic. Finance research letters, 38, 101701.

[27]Löbler, H. (2014). When trust makes it worse—Rating agencies as disembedded service systems in the US financial crisis. Service Science, 6(2), 94-105.

[28]Bakshi, R. K., Kaur, N., Kaur, R., & Kaur, G. (2016, March). Opinion mining and sentiment analysis. In 2016 3rd international conference on computing for sustainable global development (INDIACom) (pp. 452-455). IEEE.

[29]Chapelle, O., Schölkopf, B., & Zien, A. (2006). A discussion of semi-supervised learning and transduction. In Semi-supervised learning (pp. 473-478). MIT Press.

[30]Markowitz, H. M. (1968). Portfolio selection. Yale university press.

[31]Schmitt, N., & Westerhoff, F. (2017). Herding behaviour and volatility clustering in financial markets. Quantitative Finance, 17(8), 1187-1203.

[32]Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2016). Investor sentiment, beta, and the cost of equity capital. Management Science, 62(2), 347-367.

[33]Sen, J., & Chaudhuri, T. D. (2018). Understanding the sectors of Indian economy for portfolio choice. International Journal of Business Forecasting and Marketing Intelligence, 4(2), 178-222.

[34]Jhunjhunwala, A., & Chaudhuri, T. D. (2021). Innovation, growth and value creation: a study of Indian companies. International Journal of Business Innovation and Research, 25(3), 328-352.

[35]Jareño, F., de la O González, M., Tolentino, M., & Sierra, K. (2020). Bitcoin and gold price returns: a quantile regression and NARDL analysis. Resources Policy, 67, 101666.

[36]Daudert, T. (2021). A multi-source entity-level sentiment corpus for the financial domain: the FinLin corpus. Language Resources and Evaluation, 1-24.

[37]Sinha, N. R. (2016). Underreaction to news in the US stock market. Quarterly Journal of Finance, 6(02), 1650005.

[38] Gori, M., Monfardini, G., & Scarselli, F. (2005, July). A new model for learning in graph domains. In Proceedings. 2005 IEEE International Joint Conference on Neural Networks, 2005. (Vol. 2, pp. 729-734). IEEE.

[39] Milosevic, N. (2016). Equity forecast: Predicting long term stock price movement using machine learning. arXiv preprint arXiv:1603.00751.

[40] Pang, X., Zhou, Y., Wang, P., Lin, W., & Chang, V. (2020). An innovative neural network approach for stock market prediction. The Journal of Supercomputing, 76(3), 2098-2118.

[41] Sun, A., Lachanski, M., & Fabozzi, F. J. (2016). Trade the tweet: Social media text mining and sparse matrix factorization for stock market prediction. International Review of Financial Analysis, 48, 272-281.

[42] Hamilton, W. L., Ying, R., & Leskovec, J. (2017). Representation learning on graphs: Methods and applications. arXiv preprint arXiv:1709.05584.

[43] Koyano, S., & Ikeda, K. (2017, November). Online portfolio selection based on the posts of winners and losers in stock microblogs. In 2017 IEEE Symposium Series on Computational Intelligence (SSCI) (pp. 1-4). IEEE.

[44]Abe, M., & Nakayama, H. (2018, June). Deep learning for forecasting stock returns in the cross-section. In PacificAsia conference on knowledge di

[45]Bao, W., & Liu, X. Y. (2019). Multi-agent deep reinforcement learning for liquidation strategy analysis. arXiv preprint arXiv:1906.11046.

[46]Yu, P., Lee, J. S., Kulyatin, I., Shi, Z., & Dasgupta, S. (2019). Model-based deep reinforcement learning for dynamic portfolio optimization. arXiv preprint arXiv:1901.08740.

[47]Batra, R., & Daudpota, S. M. (2018, March). Integrating StockTwits with sentiment analysis for better prediction of stock price movement. In 2018 International Conference on Computing, Mathematics and Engineering Technologies (iCoMET) (pp. 1-5). IEEE.

[48]Zhang, Z., Shen, Y., Zhang, G., Song, Y., & Zhu, Y. (2017, November). Short-term prediction for opening price of stock market based on self-adapting variant PSO-Elman neural network. In 2017 8th IEEE International Conference on Software Engineering and Service Science (ICSESS) (pp. 225-228). IEEE.

[49]Firdaus, M., Pratiwi, S. E., Kowanda, D., & Kowanda, A. (2018, October). Literature review on artificial neural networks techniques application for stock market prediction and as decision support tools. In 2018 Third International Conference on Informatics and Computing (ICIC) (pp. 1-4). IEEE

[50]Tekin, S., & Çanakoğlu, E. (2018, May). Prediction of stock returns in Istanbul stock exchange using machine learning methods. In 2018 26th Signal Processing and Communications Applications Conference (SIU) (pp. 1-4). IEEE.

[51]Othan, D., Kilimci, Z. H., & Uysal, M. (2019, December). Financial sentiment analysis for predicting direction of stocks using bidirectional encoder representations from transformers (BERT) and deep learning models. In Proc. Int. Conf. Innov. Intell. Technol. (Vol. 2019, pp. 30-35)

[52]Kilimci, Z. H. (2020). Financial sentiment analysis with Deep Ensemble Models (DEMs) for stock market prediction. Journal of the Faculty of Engineering and Architecture of Gazi University, 35(2), 635-650.