Incorporating Combinations of Sentiment Scores Of Financial News And MLP-Regressor For Stock Prediction.

Junaid Maqbool[1], Preeti Aggarwal[1], Ravreet Kaur[1]

[1] UIET, CSE Department, Panjab University, Chandigarh, India
maqbooljunaid@gmail.com

Abstract.

The stock market is very volatile as it depends on political, financial, environmental, and various internal and external factors along with historical stock data. Such information is available to people through microblogs and news and predicting stock price merely on historical data is hard. The high volatility emphasizes the importance to check the effect of external factors on the stock market. In this paper, we have proposed a machine learning model where the financial news is used along with historical stock price data to predict upcoming prices. The paper has used four algorithms to calculate various sentiment scores and used them in different combinations to understand the impact of financial news on stock price as well the impact of each sentiment scoring algorithm. Experiments have been conducted on ten-year historical stock price data as well financial news of four different companies from different sectors to predict next day and next week stock trend and accuracy metrics were checked for a period of 10, 30, and 100 days. Our model was able to achieve the highest accuracy of 0.90 for both trend and future trend when predicted for 10 days. This paper also performs experiments to check which stock is difficult to predict and which stocks are most influenced by financial news and it was found Tata Motors an automobile company stock prediction has maximum MAPE and hence deviates more from actual prediction as compared to others.

Keywords: Stock prediction, News sentiment analysis, MLP Regressor, forecasting , Financial news

Declarations (not applicable)

Funding (not applicable)

Conflicts of interest/Competing interests (not applicable)

Availability of data and material (data is available)

Code availability (custom code is available)

1. INTRODUCTION :

Stock prediction has always been one of the challenging problems of economists, statisticians, and other financial experts as it is a vital component of a country’s economy. The stock market is an area where stocks can be traded, transferred, and distributed. The stock market gives companies a chance of expanding and raising money through Initial Public Offerings (IPO)[1]. Investors can invest in stocks of various companies and can make money if they will be able to decide when to buy and when to sell particular stocks. The stock market being very volatile as the prices of stocks of particular companies are dynamic and keep changing depending on the volume of shares bought and sold in the market. The market is influenced by national policies, global and regional economics, as well as psychological and human factors[2], therefore external factors like social media and financial news have either positive or negative effects on stock prices. To gain profits stock trader needs to sell the stocks whose prices are expected to decrease and buy or hold the shares whose prices are expected to increase in near future[1]. Traditionally two approaches have been used for stock price prediction viz fundamental analysis, which depends on the research of company's fundamentals like annual growth rates, previous dividend shares provided, market position, new contracts of company, revenue and expenses[3], and technical analysis which focuses on historical price data and use historical price charts to find patterns and make prediction[4]. Technical analysis is based on Dow theory[5]. Stock price prediction has attracted researchers from various fields like computers science, economics, statistics, and operations research[6].

A large number of studies are currently active on the subject of stock prediction. Data scientists started employing machine learning algorithms to develop stock prediction models. Previous research has employed historical [7][8][9], social media[10][11], or news[12][13] data to predict the stock market using machine learning algorithm. Different prediction systems have been proposed to help investors to make trading decisions for buying or selling the stock using one or other type of data[1]. Machine learning models based on Artificial Neural Network (ANN)[14], Bayesian Network[15], Multi-Level Perceptron(MLP)[16], Support Vector Machines(SVM)[17], and Recurrent Neural Network-based Long Short Term Memory(LSTM)[18] have already been utilized to predict the future trend of stocks as well stock prices. different stock markets around the world react differently to the period of crisis and other political and financial situations hence cannot be always predicted by simple trading strategies[19].

The motivation for this study is to harness and understand the effect of financial news on the stock price trend and to predict the future stock trend based on the financial news sentiments by training our model using financial news sentiments and historical stock data. There are various ways to calculate the sentiments of the text. This paper has explored three types of sentiment scores along with MLP Regressor to predict the change in stock trend and to understand the effect of each sentiment analyzer independently as well in combination with other sentiment scores. The three sentiment scoring methods are Valance Aware Dictionary And Sentiment Reasoner(VADER)[20] from NLTK[21], TextBlob[22] and Flair[23] both from NLP[24]. This paper also uses the parameter *label* which uses keywords to check if any news is about or related to the company whose stock price predictions are under consideration. This paper predicts the trend on the following day using the previous day's price and sentiment scores and comparing the prices of the next day with the previous day and future trend by comparing the stock prices of one day with the price after n days. The model has been tested on four different kinds of companies from different sectors to evaluate the model on different data and check the validity of the model in a variety of fields.

The major contributions of this research are :

- Proposing an MLP Regressor model with financial news sentiments and historical stock price data to predict the future trend of stock price and check the accuracy metrics for each case and check the consistency of the model.
- Different sentiment scores are used along with MLP – Regressor to check the effect of each sentiment scoring method on the stock price prediction and using the sentiment scoring algorithms independently as well in combinations and to compare which combination of sentiment scores have more impact on the stock price movement.

- Different companies are tested against the mentioned model to check the sectors and companies which are most influenced by financial news and to check the stocks which are easily predicted and the ones which are difficult to predict

The remaining part of this paper is organized as follows: Existing work in stock prediction in Section 2. In Section 3 we explain the research methodology and explain all steps in the research in detail. In section 4 we provide the experimental results and discussions and then in section 5, we provide the conclusion and suggestions for future work in this field.

2. RELATED WORK

The models which take the technical analysis approach mostly take prediction as a classification problem where market patterns are learned from historical stock price data and the models which work to predict exact stock prices are termed as predictive regression in economic litreture[25]. The simple and naive approaches are generally unable to learn long-term trends and suffer from overfitting when applied to real-world problems.

The main aspects of literature are the following:

1. Different machine learning algorithms and different types of data such as historical price data, social media data, political and financial news data for stock market prediction.
2. Different sentiment analysis techniques have been used by researchers to classify and score texts.
3. It is evident that public opinions and emotions as well the regional and global news have a direct effect on stock market price fluctuation.

3.1 Sentiment analysis

sentiment analysis has gained extreme importance because of the availability of huge textual data on social media, news platforms, shopping and movie reviews, and elsewhere on the internet. This textual data can be mined to find opinions of individuals in various areas and to achieve the analysis on this huge data machine learning and data mining are of extreme importance. Therefore a lot of research is done to find the opinion of users in different fields using sentiment analysis[1]. Classification of tweets can be made based on their content. The sentiment analysis is being explored based on rules, lexicons, and machine learning categorization methods which can classify tweets as positive or negative or neutral based on sentiment towards the field in the study. Support vector machine(SVM), Naive Bayes (NB), Maximum Entropy (ME) were used among machine learning techniques feature scaling and word count approaches were tried for lexicon-based techniques. Bag of Words (BoW) with N-Gram achieved better performance over Part-Of-Speech linguistic annotations[26][27]. While evaluating tweets using NB it was found the tweets are very concise and the opinion in tweets are structured and non-uniform, so can be classified into positive, negative and neutral classes[28].

Having millions of tweets and news articles available but not all of them are always related. Tweets and articles regarding movie reviews will not have any effect on the stock market and hence while dealing with any specific problem the selected tweets which are having influence over such research should be used. Comparative analysis of NB, ME, and SVM using unigram features and bigram features and combination of both to classify movie review data from Twitter it was found SVM classifier performs better than other classifiers[29]. On tweets related to technology stocks like Facebook, Google, etc. Logistic Regression (LR) and neural networks with weighing schemes Term Frequency (TF) and TF Inverse Document Frequency (TF-IDF) were applied and it was found the accuracy of classifiers do not vary much but empirical experiments showed TF-IDF outperform TF[30].

The stock market is influenced by the news as it conveys the events which have an impact on the stock market directly. The news data was also classified into upward, neutral and downward classes by using

SVM on stock data and news related to concerned companies, and a direct correlation is found between stock price and news[31]. The stock-related news when auto categorized and stock-related information is extracted has a direct relationship with the stock behavior [32]. Some sentiment scoring methods which are predefined in important libraries like NLTK[21] and NLP[23] are as:

- VADER a rule-based general sentiment analysis method uses a combination of qualitative and quantitative methods which validate empirically a list of lexical features to calculate sentiment score as negative, positive, neutral, and compound. VADER performs better than most highly regarded sentiment analysis tools.[20][21]
- TextBlob predefined in NLP gives sentiment score as polarity and subjectivity where polarity classifies a statement as positive and negative giving score as a float in the range of [-1,1], and subjectivity gives information regarding the text if it is an opinion, emotion, or factual information [24][33].
- FLAIR is an NLP framework that facilitates sequence labeling and text classification. The main function is to provide a unified interface for very different types of works and embeddings in the document.[23]

3.2 Stock market prediction using stock market historical data

The models which operate on the principle of technical analysis to predict stock price take prediction as a classification problem where the market pattern is learned from historical time series data[25]. Before the social media data and financial news data as well algorithms to score textual data were not widely available researchers used to apply various machine learning algorithms on the historical stock price for predictions[27]. Machine learning models have shown that Artificial Neural Networks (ANN) can learn input-output relationships and help to make close forecasts on daily closing prices when trained on the same data[34]. A machine learning model with Particle Swarm Optimization (PSO) to optimize Least Squares (LS)-SVM using financial technical indicators like relative strength index, money flow index, etc. for stock prediction was able to overcome an over-fitting problem like in ANN[7]. Since ANN, SVM and other models were still unable to predict the chaotic fluctuations of the stock market because of the absence of memory element hence unable to remember the long-term trend. Long Short Term Memory (LSTM) based on Recurrent Neural Network (RNN) was used to learn the stock market trend and it was able to predict the opening price while learning long-term patterns and performed better than earlier models[18]. The hybrid model of Empirical Wavelet Transform(EWT) along with LSTM and PSO performed better than other deep learning models and better than any single model used[35]. An ensemble of the Deep Q-learning model was trained to maximize the profit over time without being prone to market ups and downs and being flexible against complex stock fluctuations[19]. Attention-based bi-directional LSTM was used on the Chinese stock exchange market which considered real transaction records and used Convolutional Neural Network (CNN) to extract daily group trading vector and fed into Deep Stock-trend Neural Network (DSPNN) for prediction. The model outperformed LSTM because of the attention mechanism and bi-directional structure of DSPNN[36].

3.3 Stock market prediction using social media data and financial news

Social media platforms allow people to share their moments, news, opinions about anything. Since investors also post financial analysis concerning financial securities. People also react and post regarding any news concerning stock companies which can be mined and classified to understand the emotion and sentiment of investors about the market. Financial news, political news, and social media have a direct effect on stock prices. since all of the data is available online and when used along with the historical stock prices and machine learning models like ANN the prediction accuracy and the trend of prediction improved significantly [37]. Stock-related tweets are collected and using SVM their average marginal values are obtained and then closing stock price is predicted using Regression Trees[10]. The LSTM's point to point prediction is closest to actual values and increasing the number of hidden layers didn't make any significant impact on accuracy, after implementing sentiment analysis on tweets it was found tweets affect stock price more when polarizing news about a company floats in media sources[38].

The stock market is influenced by political situations, regional policies, and financial news. Incorporating stock time series data with financial news and using neural networks it was found stock price change has a strong relationship with financial news articles. Among Time series prediction models like Auto-Regressive Integrated Moving Average (ARIMA), RNN, and Facebook Prophet was used along with financial news data. RNN performed better and a correlation between news textual data and stock price direction was found[39]. Using the dictionary approach which was particularly created for the pharmaceutical market sector by researching and leveraging domain expertise to calculate the sentiments of news articles and used with machine learning models achieved higher directional accuracy[40]. Positive correlations exist between stock trends of companies that belong to the same sector and the effect of political news range from 10% - 20%. The impact of any political event is most effective on the 5^{th} day from the date of occurance[27]. Combing sentiments of social media and financial news, the highest accuracy decreases but overall accuracies of most classifiers increase. The spam tweet reduction and feature selection have a positive impact on the performance of classifiers. The prediction accuracy of individual classifiers increases when the voting ensemble method on an ensemble of predictions of individual classifiers was used[1].

3. Research Methodology

This section will describe all the steps taken in our framework proposed for stock prediction. Our proposed framework includes the following steps

3.1. Data Collection

Historical stock data is available on Yahoo Finance[1]. Stock price data of needed companies can be collected from Yahoo Finance for the selected time in .csv file format. The data files downloaded have values of Open, High, Low, Close, Volume, and Adjusted Close for each date the stock market was open. The features represent the Opening stock price, the highest price of the stock in that day, the lowest stock price, Closing price, volume of shares traded, and Adjusted Closing price which represents the Closing price of the stock after paying dividends to investors respectively for a specific date[1]. Stock historical price data of HDFC bank is presented in Table 1.

Table 1: Historical HDFC Bank stock price data

Date	Open	High	Low	Close	Adj close	volume
04-01-2010	13.275	13.348	13.163	13.346	12.47663	2117000
05-01-2010	13.277	13.403	13.25	13.403	12.52991	1906000
06-01-2010	13.25	13.51	13.25	13.463	12.58601	1293000
07-01-2010	13.357	13.689	13.35	13.678	12.787	2944000

The historical time series stock data of four companies from different sectors (Table 2) was obtained and used in this study.

Table 2: List of companies understudy

Name of Company	Company sector	Data from	Data to
Reliance	Telecom	Jan 2010	May 2020
Tata Motors	Automobile	Jan 2010	Jan 2020
Tata Steel	Metal	Jan 2010	Jan 2020
HDFC	Banking	Jan 2010	Jan 2020

Four different companies from varying sectors were chosen to check the generalizability of the proposed model. The companies were taken into consideration to check which sector or company is most influenced by the financial news articles and which sector is easier to predict. Indian Financial news for the time range of historic data used was also collected and historical price data was merged with the financial news data by adding all the news on a specific date from financial news data to the historical data. Headlines and a short description of news for each date were concatenated together. All financial news headlines were added without segregating news of different sectors or companies. To understand the effect of related news and general financial news some keywords related to the company were used to check if that news is regarding a particular company and stored as a new feature *label* which equals zero when news is not related to the specific company and one otherwise.

3.2. Sentiment analysis

Sentiment analysis of financial news articles is done using three different algorithms to calculate sentiment scores from each algorithm. The algorithms used include VADER [20] from NLTK[21] which give scores like positive, negative, neutral, and compound. VADER checks Polarity that is if a statement is positive or negative as well as the intensity of the emotion by checking how intensely the statement is positive, negative, or neutral[20]. TextBlob [33] from NLP[24] scores the subjectivity and polarity of the financial articles and then Flair from NLP [23] which scores each sentence in the textual data and returns an array of the score of each statement. In this paper, the score of individual statements is summed to provide a feature *score sum* that represents the complete Flair score of financial news. All these sentiment scores were used as features to understand the effect of sentiments on stock price data as well as understand how well each sentiment score represents the emotions of people towards stock data. In this paper, we have used the above three sentiment scoring sets individually and then in combination with each other to find the best and most effective sentiment score algorithm or the combination of features. The algorithms and the sentiment scores under them and their significance are listed in Table 3.

Table 3. Features from different algorithms

Algorithm/ Library	Sentiment score	Range	Significance
VADER	Positive	[0-1]	The proportion of textual data that fall in the positive category
	Negative	[0-1]	The proportion of textual data that fall in the Negative category
	Neutral	[0-1]	The proportion of textual data that fall in the Neutral category
	Compound	[-1,1]	Calculates the sum of all lexicon ratings which have been normalized between [-1,1]
	Subjectivity	[0,1]	Subjectivity tells us the extent to which a statement is subjective or objective where 0.0 represents very

TextBlob			objective and 1.0 represents highly subjective. The higher subjectivity means text contains personal opinions rather than factual information.
	Polarity	[-1,1]	Calculates the sentiment of a statement where -1 represents a negative statement and +1 is a positive statement.
FLAIR	score/ score_sum	[-1,1]	A state-of-the-art NLP model applied to text generally individual statements to calculate positive or negative comments using a pre-trained model. Score_sum is calculated by summing all the individual sentence scores of each textual section.

3.3. Feature Extraction

We have used various features as input in this paper. Besides the sentiment scores from the given three algorithms and closing price and previous day closing price from the historical stock price data. closing price and previous day closing price is normalized between 0 and 1.

Trend and *Future trends* are extracted by subtracting stock closing price on two dates. Trend and future trends have nominal values of positive, negative, and neutral. The criteria for calculating these values are given in the following equation.

$$trend = \begin{cases} Positive \quad if\ C_d - C_{d-1} > 0 \\ Neutral \quad if\ C_d - C_{d-1} = 0 \\ Negative \quad if\ C_d - C_{d-1} < 0 \end{cases} \tag{1}$$

The trend represents the stock movement on the next day of trade. C_d is the closing price on day d and C_{d-1} is the stock price on day d-1. The trend represents the one-day stock movement trend. If the stock price of one day is more than the previous day then the trend is said to be positive and means the stock price is moving up. If the closing price is less than the closing price of the previous day the trend is negative and stock means the stock price is moving down and if the stock price doesn't change on two days the trend is neutral.

The future trend represents a change in stock movement after n days. In our research, we have taken n as five. As the stock market is open five days a week so our *future trend* generally gives us a stock trend movement of one week. The future trend is calculated by subtracting the stock price of day d from day d+n. This gives the future trend on the day (d+n). If the difference is positive means the trend will be positive after n days and if negative then it will be negative hence the stock price will move down after n days. The below equations can be used to calculate future trend

$$future\ trend = \begin{cases} Positive \quad if\ C_{d+n} - C_d > 0 \\ Neutral \quad if\ C_{d+n} - C_d = 0 \\ Negative \quad if\ C_{d+n} - C_d < 0 \end{cases} \tag{2}$$

Where C_{d+n} is the stock price on the day (d+n) and C_d is the stock price n days before (d+n). And in this paper, we are checking future trends for up to one week. Hence we will check the impact of financial news for one-week prediction in the future.

One more feature used is the *label* which represents if the news is regarding any particular company or not by simply checking the news for certain keywords specific for each company. The label is **true** when a particular date has a piece of news specific to the company under consideration otherwise **false**.

3.4. Final dataset

A final dataset is complied with historical time series stock price data, financial news sentiments calculated by the discussed algorithm for each day, label, trend, and future trend. All of these features make up the final dataset with some rows shown in **Table 4.** In the table, we represent only these features that have been used in the prediction models.

Table-4. A view of final dataset of HDFC stock price with sentiment scores

Date	Close	Label	Subjectivity	Polarity	Compound	Negative	Neutral	Positive	Score_sum
04-01-2010	13.346	1	0.392845	0.026326	0.9349	0.01	0.898	0.091	0.653
05-01-2010	13.403	1	0.348687	0.05759	0.8074	0.076	0.806	0.118	-1
06-01-2010	13.463	1	0.323457	0.083025	0.9756	0.018	0.896	0.086	0.608
07-01-2010	13.678	1	0.281247	0.063513	0.9896	0.038	0.861	0.101	-1.07
08-01-2010	13.719	1	0.368182	-0.01205	0.8969	0.07	0.839	0.091	-1.03
11-01-2010	13.51	1	0.355764	0.013681	0.7351	0.061	0.856	0.083	-1
12-01-2010	12.812	1	0.34876	0.05221	0.9906	0.02	0.899	0.081	-0.973

The combination of different features at once was input to the model along with the previous day's closing price to predict the closing price of the stock market. These accuracy metrics are compared to understand the impact of various sentiment scores on the stock price prediction.

3.5. Applying machine learning classifier

In this research, we have used MLP-Regressor [34] to predict the stock closing price. We have used different sets of features for predicting the stock closing price and then used one set of features with different company's data to understand the generalizability of the model. The model used is shown in Fig 1.

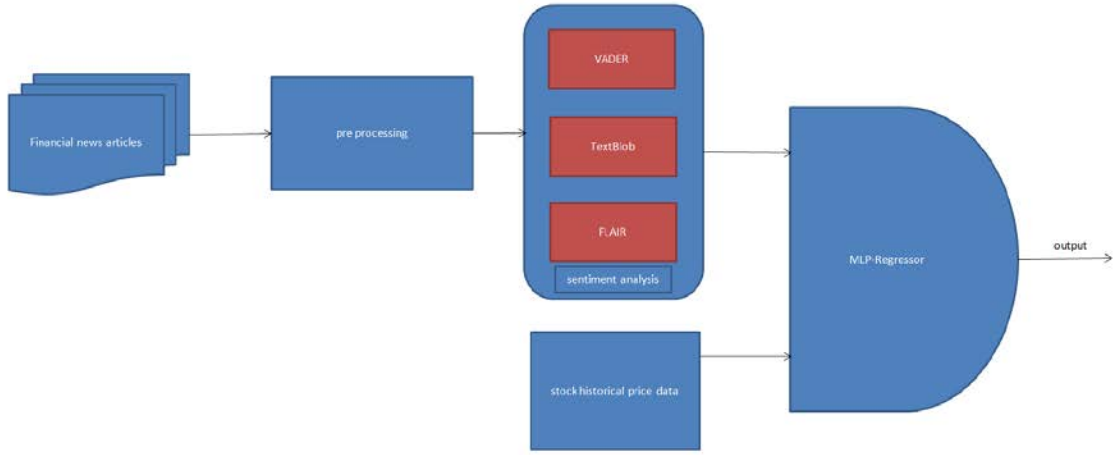

Fig 1. MLP- Regressor along with sentiment analysis model

Financial news articles are processed and then the sentiment is computed and along with these sentiments the historical stock price is input to the MLP-Regressor to calculate the output from the model.

3.6. Performance evaluation of model

The metrics which are used to check the performance of the model and evaluate the ability of the model to predict the stock price are discussed in this section. this paper evaluates the effectiveness of the model to predict the stock market on the next day called a *trend.* And also the ability to predict *future trends* which shows how well the model predicts the stock movement in the future which is roughly a week taken in this paper. The future trend checks the effect of news in the future. While predicting the stock price there are two things that are to be evaluated, stock price movement and stock price. The effectiveness of stock movement can be checked from trends and future trends. And the ability of the model to predict stock price can be checked by comparing predicted stock price with actual stock price and in this paper, we have used MAPE to check the error in stock price prediction without considering stock direction. The accuracy metrics used in this paper are defined as follows.

Accuracy is a popular metric used in classification problems. It represents the number ratio of correctly classified values to a total number of classified values [19]. The trend and future trend are classified in three classes viz positive negative and neutral represented by 1,-1, and 0 respectively. If the trend is negative it represents the decision to sell the stocks or not buy, and if the trend is positive or neutral the decision is to buy/hold (1/0). And hence accuracy is checked for binary classification viz buy/hold or sell(-1).

Table 5. Trend values for performance metric calculation

Original Trend	**Predicted Trend**	**Classification group**
0/1	0/1	True Positive (TP)
0/1	-1	False Negative (FN)
-1	0/1	False Positive (FP)
-1	-1	True Negative (TN)

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (3)$$

This is to be noted the two values are clubbed together for upward or static trend as 0/1.
Precision represents the ratio of actual positive among a total number of positively classified.

$$Precision = \frac{TP}{TP+FP} \qquad (4)$$

Recall is a ratio of actual positives among all real positives.

$$Recall = \frac{TP}{TP+FN} \qquad (5)$$

F1-score: is the harmonic mean of recall and precision. It is a function of both and hence represents the overall scores of a model.

$$F1-Score = \frac{2*precision\ *recall}{precision\ +recall} \qquad (6)$$

Mean Absolute Percentage Error (MAPE) average relative error of forecast in percentage hence one of the most popular prediction accuracy metrics [41][39].

$$MAPE = \frac{100}{n}\sum_{j=1}^{n}\left|(y_j - y'_j)/y_j\right| \tag{7}$$

Where y_j is the original value and y'_j is the corresponding predicted value.
Accuracy, Precision, Recall, and F1-Score have been used to check the metrics of trend as well future trend which explains how well the model can predict the immediate stock movement and future stock movement.

4. Experimental results and discussion

The model MLP-Regressor is tested with a different combination of sentiments discussed in Table 3. In this paper, the impact of each sentiment analyzing algorithm was tested along with the MLP-Regressor. The trend accuracy, future trend accuracy, and MAPE (Table 9) were checked for all combinations. The metrics were recorded for 10 days, 30 days, and 100 days. The effectiveness of models was tested for every combination of HDFC data to understand the impact of all feature set combinations. the graphs for all combinations are also plotted to understand the way every model behaves in stock forecast prediction. The prediction metrics for trend and F-trend (future trend) of HDFC data on various models for 10 days are presented in Table 6, for 30 days in Table 7, and 100 days in Table 7. The machine learning model used in all experiments is MLP-Regressor and sentiment combinations used are mentioned in each table.
Figs (2-9) each represent the graph of prediction of HDFC using each model. The difference in each model is the number and combination of features as input.

Table 6. HDFC data along with for 10 days trend

Sentiment combinations	Precision		Recall		Accuracy		F1-Score	
	Trend	F-Trend	Trend	F-Trend	Trend	F-Trend	Trend	F-Trend
VADER	0.857	0.875	0.857	1.0	0.8	0.9	0.857	0.933
TextBlob	0.83	0.7	0.714	1.0	0.7	0.7	0.769	0.823
FLAIR	0.875	0.875	1.0	1.0	0.9	0.9	0.933	0.933
VADER +TextBlob	1.0	0.75	0.857	0.857	0.9	0.7	0.92	0.79
VADER+ FLAIR	0.6	0.77	0.42	1.0	0.4	0.8	0.5	0.875
FLAIR +TextBlob	1.0	0.77	0.85	1.0	0.9	0.8	0.92	0.875
VADER + TextBlob +FLAIR	0.8	0.77	0.57	1.0	0.6	0.8	0.66	0.875
VADER + TextBlob +FLAIR +Label	1.0	0.77	0.57	1.0	0.7	0.8	0.72	0.875

Table 6 shows that the highest prediction accuracy for the next-day trend can be seen in FLAIR (F), VADER + TextBlob (V+T), and F+T models which is equal to 0.9. it is also observed recall for future trends almost remains highest in every model except in V+T.
While checking the accuracy metrics for 30 days in Table 7 it is observed maximum accuracy of 0.73 is observed in next day prediction with F+T and V+T+F, TextBlob (T) and Flair(F) each individually show the same accuracy for future trend and highest MAPE is observed in TextBlob case for all the test portion.

In Fig 3 we can see the uneven spikes in prediction price while using TextBlob justifying the highest MAPE (Table 9).

Table 7. HDFC data along with for 30 days trend

Sentiment combinations	Precision		Recall		Accuracy		F1-Score	
	Trend	F-Trend	Trend	F-Trend	Trend	F-Trend	Trend	F-Trend
VADER	0.714	0.714	0.625	0.666	0.66	0.7	0.666	0.689
TextBlob	0.66	0.705	0.625	0.8	0.63	0.73	0.645	0.75
FLAIR	0.705	0.733	0.75	0.73	0.7	0.73	0.72	0.73
VADER +TextBlob	0.73	0.71	0.687	0.66	0.7	0.7	0.70	0.68
VADER+ FLAIR	0.61	0.66	0.5	0.66	0.56	0.66	0.55	0.66
FLAIR +TextBlob	0.78	0.63	0.68	0.8	0.73	0.66	0.73	0.70
VADER + TextBlob +FLAIR	0.714	0.73	0.625	0.73	0.66	0.73	0.66	0.73
VADER + TextBlob +FLAIR +Label	0.85	0.8	0.75	0.8	0.8	0.8	0.79	0.8

Trend and Future trend accuracy when checked for 100 days (Table 8) to understand the long term effectivity of the model it is observed the model was able to predict future trends with the highest accuracy of 0.75 individually and hence shows the effect of FLAIR sentiment in case of stock prediction is of considerable factor. While the next-day trend was predicted best by the F+T model. From each model, we can see future trend prediction is more predictive with sentiment scores than the next-day trend.

Table 8. HDFC data along with for 100 days trend

Sentiment combinations	Precision		Recall		Accuracy		F1-Score	
	Trend	F-Trend	Trend	F-Trend	Trend	F-Trend	Trend	F-Trend
VADER	0.56	0.77	0.55	0.76	0.53	0.71	0.56	0.76
TextBlob	0.6	0.77	0.55	0.76	0.56	0.71	0.57	0.76
FLAIR	0.58	0.81	0.62	0.77	0.56	0.75	0.60	0.79
VADER +TextBlob	0.62	0.77	0.62	0.74	0.6	0.7	0.62	0.75
VADER+ FLAIR	0.58	0.76	0.57	0.76	0.55	0.7	0.57	0.76
FLAIR +TextBlob	0.66	0.72	0.59	0.74	0.62	0.66	0.62	0.73
VADER + TextBlob +FLAIR	0.55	0.77	0.53	0.71	0.52	0.69	0.54	0.74
VADER + TextBlob +FLAIR +Label	0.63	0.76	0.61	0.73	0.6	0.69	0.622	0.74

MAPE shows how closely the stock price can be predicted to the original price and it is the mean percentage of relative error and is checked for the complete test set. We can see in V+T+F and

V+T+F+Lable (L) later shows less MAPE than V+T+F proving the effectivity of the label in a positive direction for a stock price forecast.

Table 9. MAPE for each model

Sentiment Combination	VADER	TextBlob	FLAIR	VADER +TextBlob	VADER + FLAIR	FLAIR +TextBlob	VADER + TextBlob +FLAIR	VADER + TextBlob +FLAIR +Label
MAPE	1.77	2.32	1.48	1.64	1.74	1.55	2.00	1.83

In fig 3,5,7,8 and 9 we can see using TextBlob sentiment causes uneven prediction and hence affects the model to predict the amount of change in stock price causing the increase in MAPE. From Fig 2 and 4 we can observe the VADER and Flair can follow the trend more closely. Following figures Fig 2-9 show how closely some combinations of features are able to follow the trend and how combinations with TextBlob and some models with more features have exaggerated fluctuations and more complex than the original plot.

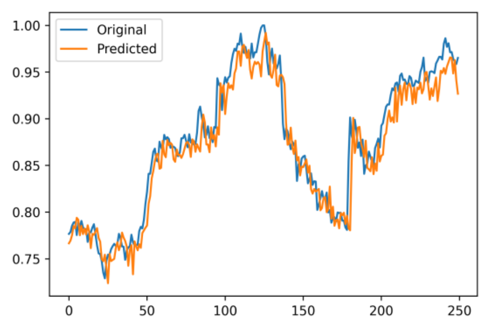

Fig 2. HDFC with VADER plot

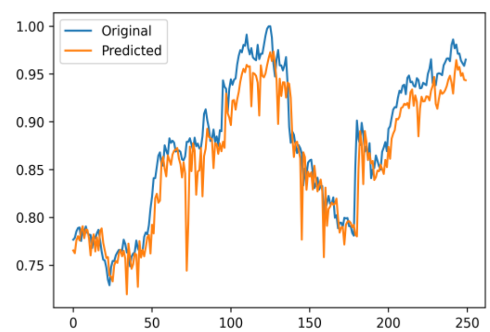

Fig 3. HDFC with Textblob

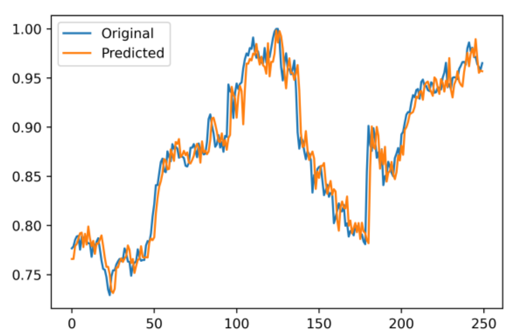

Fig 4. HDFC with FLAIR

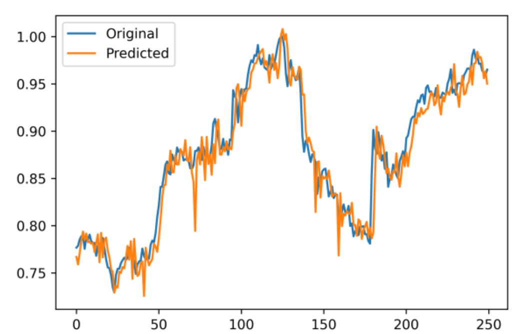

Fig 5. HDFC with VADER and TextBlob

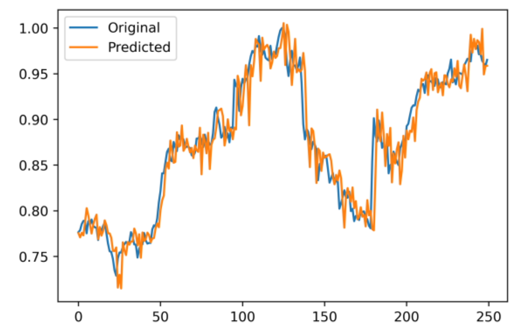

Fig 6. HDFC with VADER and Flair

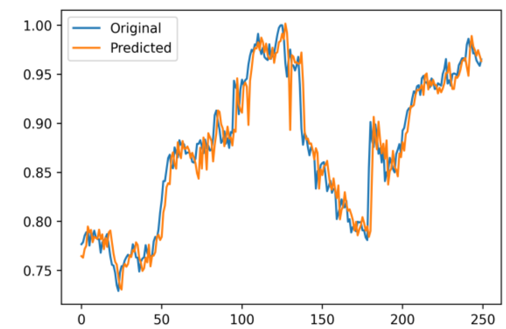

Fig 7. HDFC with FLAIR and TextBlob

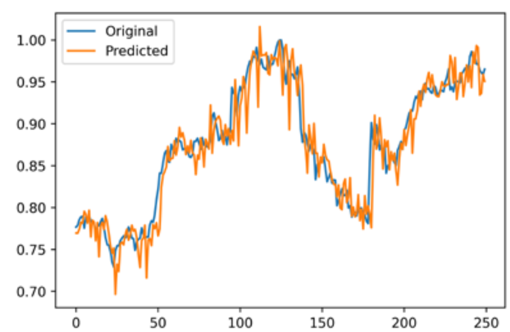

Fig 8. HDFC with Vader, flair, and textblob

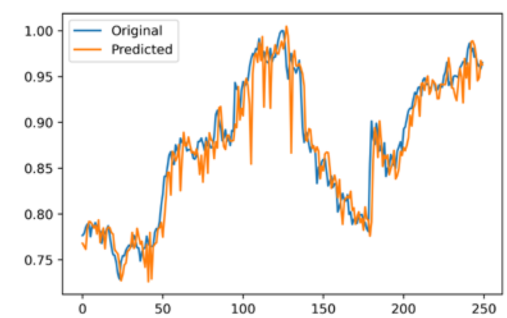

Fig 9. HDFC with flair, Vader,textblob, and label

To understand the generalizability of the model and to understand which stocks are more affected by financial news sentiments, feature combinations from Table 3 viz Positive, Negative, Neutral from VADER and score_sum from Flair were used to check the prediction metrics for Reliance (Fig 10), Tata Steel (Fig 11), Tata Motors (Fig 12) and HDFC (Fig 13) for 10, 30 and 100 days (Table 10).

Table 10. Accuracy metrics of Reliance, Tata Motors, and Tata Steel

Company	MAPE	No. Of Days	Precision		Recall		Accuracy		F1-Score	
			Trend	F-Trend	Trend	F-Trend	Trend	F-Trend	Trend	F-Trend
Reliance	2.57	10	0.75	1.0	0.75	0.714	0.8	0.8	0.75	0.83
		30	0.66	0.61	0.66	0.68	0.66	0.6	0.66	0.64
		100	0.53	0.57	0.55	0.61	0.58	0.65	0.54	0.59
Tata Motors	4.71	10	0.75	0.88	0.5	0.88	0.6	0.8	0.6	0.88
		30	0.46	0.68	0.4	0.72	0.46	0.63	0.42	0.70
		100	0.59	0.71	0.53	0.73	0.57	0.71	0.56	0.72
Tata Steel	2.55	10	0.25	0.83	0.33	0.71	0.5	0.7	0.28	0.76
		30	0.3	0.55	0.3	0.55	0.53	0.73	0.3	0.55
		100	0.55	0.69	0.51	0.65	0.61	0.67	0.53	0.67
HDFC	1.61	10	0.77	0.7	1.0	1.0	0.8	0.7	0.87	0.82
		30	0.68	0.62	0.68	0.66	0.66	0.63	0.68	0.64
		100	0.61	0.73	0.64	0.74	0.59	0.67	0.63	0.74

From table 10 it can be checked tata motors is having the highest MAPE among all four companies taken into consideration and we can see in Fig 11 all these uneven spikes. From Fig 10 and 12 we can see Reliance and Tata Steel are more closely following the original price plot showing the better relationship between sentiments and price fluctuation of stocks of these companies. Reliance is able to achieve 0.8 accuracies in the next day trend as well future trend for seven days (Table 10). Tata Motors MAPE as well predicted price and original price plot (Fig 11) and also HDFC plot (Fig 13) show predicted price does not follow original price closely and the correlation of financial news in more strong with Telecom company Reliance, Metal company Tata Steel as compared to Banking sector company HDFC and automobile company Tata Motors.

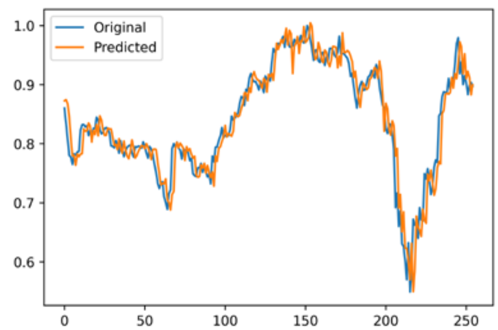

Fig 10. Reliance stock prediction

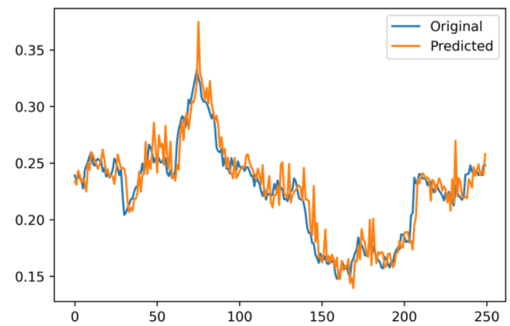

Fig 11. Tata Motors stock prediction

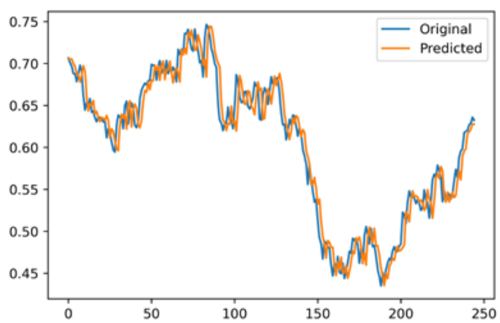

Fig 12. Tata Steel stock prediction

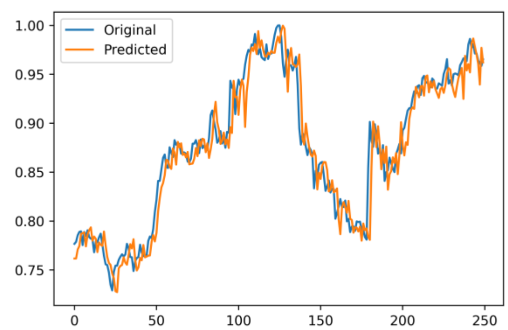

Fig 13. HDFC stock prediction

MAPE for various combinations of sentiments from Table 9 is pictorially plotted in Fig 14 and it is observed for TextBlob MAPE is maximum and causes an uneven shift in prediction prices, V+T+F shows second highest MAPE while when adding Label to same the MAPE decreases by 0.17. MAPE for various companies as in Table 10 is pictorially represented in Fig 15. It can be observed for Tata Motors MAPE is maximum hence the prediction prices will have more deviation from real price and HDFC have the lowest MAPE.

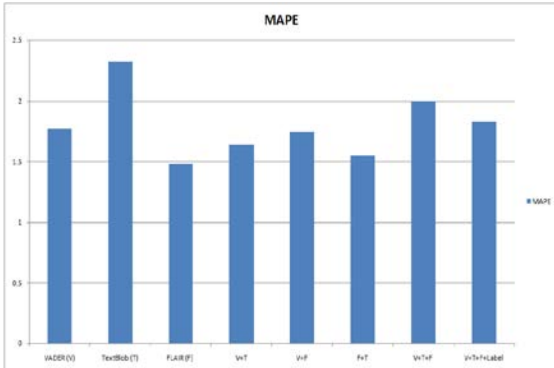

Fig 14. MAPE for different combinations of sentiments used for HDFC

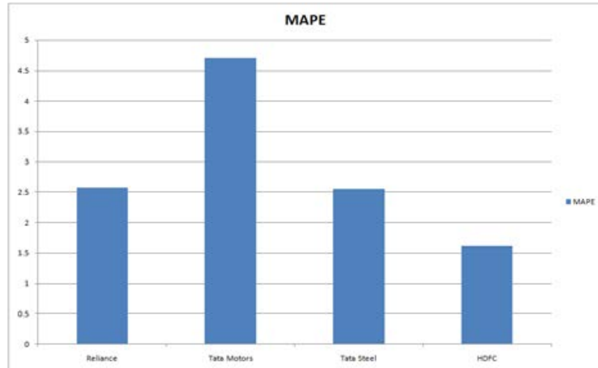

Fig 15. MAPE for different companies using the same features.

The proposed model is able to predict stock price trends even to an accuracy of 0.9 and which is comparable to the state-of-art models for stock price prediction. The model can also predict the future trend even up to the same accuracy in some cases and most cases recall remains highest and shows our model can predict actual positive among all real positives at a rate of 100% (Recall) in most cases. The model was tested with a wide range of sentiment score combinations and explores best features to be used in sentiments of financial for stock price prediction. The model when used with different companies also shows the effectiveness of the model in general and hence can be used with most stock companies and financial news to forecast the stock trend.

5. Conclusion and future work

This research paper presents a framework for stock price prediction using historical stock data and sentiments of financial news. Different combinations of sentiment scores were tested again in the machine learning models with HDFC stock data to understand the effect of each set on the stock price fluctuation. We have checked the effect of financial news sentiments on 10 days, 30 days, and 100 days of stock prediction. The accuracy of next-day stock price trend and future stock movements was observed and each set of sentiments were tested for accuracy as well MAPE to understand the effect of sentiment score on stock prices. Then a set of sentiment scores was used on four different companies to check the generalizability of the model and to see stocks of which companies are most influenced by financial news. It was also observed that using *label* helps reduce MAPE and hence fit the trend and predict stock price more accurately depicting the higher correlation between stock price and financial news about this specific company. While using TextBlob sentiments MAPE increases and uneven exaggeration in stock price change was observed while in the case of the model using Flair sentiments the MAPE was lowest. Higher MAPE in the case of Tata Motors shows less correlation among stock price of automobile companies like Tata Motors and financial news. This paper concludes using financial news sentiments along with MLP-Regressor can predict the stock price to an accuracy of 0.90 and shows a high correlation between stock price and financial news.

There are more models to be used in future studies for stock market prediction and an ensemble of some such models can also be employed. LSTM, as it has a memory element, can be used to remember the trend and sentiments can be added to increase the efficiency of the model to predict the rate of change of stock price. Machine learning models as discussed in this paper and other models can also check other combinations of individual features to understand the effect of the news on the stock price. Along with financial news, social media posts, political and geopolitical news can also be employed to predict stock prices more precisely and accurately.

6. References

[1] W. Khan, M. A. Ghazanfar, M. A. Azam, A. Karami, K. H. Alyoubi, and A. S. Alfakeeh, "Stock market prediction using machine learning classifiers and social media, news," *J. Ambient Intell. Humaniz. Comput.*, no. 0123456789, 2020, doi: 10.1007/s12652-020-01839-w.

[2] X. Pang, Y. Zhou, P. Wang, W. Lin, and V. Chang, "An innovative neural network approach for stock market prediction," *J. Supercomput.*, vol. 76, no. 3, pp. 2098–2118, 2020, doi: 10.1007/s11227-017-2228-y.

[3] I. K. Nti, A. Felix Adekoya, · Benjamin, and A. Weyori, "A systematic review of fundamental and technical analysis of stock market predictions," *Artif. Intell. Rev.*, vol. 53, pp. 3007–3057, 123AD, doi: 10.1007/s10462-019-09754-z.

[4] J. L. Wang and S. H. Chan, "Stock market trading rule discovery using pattern recognition and technical analysis," *Expert Syst. Appl.*, vol. 33, no. 2, pp. 304–315, Aug. 2007, doi: 10.1016/J.ESWA.2006.05.002.

[5] R. Singh and S. Srivastava, "Stock prediction using deep learning," *Multimed. Tools Appl.*, vol. 76, no. 18, pp. 18569–18584, 2017, doi: 10.1007/s11042-016-4159-7.

[6] J. Zhang, S. Cui, Y. Xu, Q. Li, and T. Li, "A novel data-driven stock price trend prediction system," *Expert Syst. Appl.*, vol. 97, pp. 60–69, 2018, doi: 10.1016/j.eswa.2017.12.026.

[7] O. Hegazy, O. S. Soliman, and M. A. Salam, "97F44F6Cdaa778B97Efe930F6534B3Edc92F," vol. 4, no. 12, pp. 17–23, 2013.

[8] L. Chen, Z. Qiao, M. Wang, C. Wang, R. Du, and H. E. Stanley, "Which Artificial Intelligence Algorithm Better Predicts the Chinese Stock Market?," *IEEE Access*, vol. 6, pp. 48625–48633, 2018, doi: 10.1109/ACCESS.2018.2859809.

[9] P. Ou and H. Wang, "Prediction of Stock Market Index Movement by Ten Data Mining Techniques," *Mod. Appl. Sci.*, vol. 3, no. 12, pp. 28–42, 2009, doi: 10.5539/mas.v3n12p28.

[10] P. Chakraborty, U. S. Pria, M. R. A. H. Rony, and M. A. Majumdar, "Predicting stock movement using sentiment analysis of Twitter feed," *2017 6th Int. Conf. Informatics, Electron. Vis. 2017 7th Int. Symp. Comput. Med. Heal. Technol. ICIEV-ISCMHT 2017*, vol. 2018-Janua, pp. 1–6, 2018, doi: 10.1109/ICIEV.2017.8338584.

[11] S. K. Khatri and A. Srivastava, "Using sentimental analysis in prediction of stock market investment," *2016 5th Int. Conf. Reliab. Infocom Technol. Optim. ICRITO 2016 Trends Futur. Dir.*, pp. 566–569, 2016, doi: 10.1109/ICRITO.2016.7785019.

[12] D. Lien Minh, A. Sadeghi-Niaraki, H. D. Huy, K. Min, and H. Moon, "Deep learning approach for short-term stock trends prediction based on two-stream gated recurrent unit network," *IEEE Access*, vol. 6, no. September, pp. 55392–55404, 2018, doi: 10.1109/ACCESS.2018.2868970.

[13] M. R. Vargas, C. E. M. Dos Anjos, G. L. G. Bichara, and A. G. Evsukoff, "Deep Leaming for Stock Market Prediction Using Technical Indicators and Financial News Articles," *Proc. Int. Jt. Conf. Neural Networks*, vol. 2018-July, pp. 1–8, 2018, doi: 10.1109/IJCNN.2018.8489208.

[14] E. Chong, C. Han, and F. C. Park, "Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies," *Expert Syst. Appl.*, vol. 83, no. September, pp. 187–205, 2017, doi: 10.1016/j.eswa.2017.04.030.

[15] L. S. Malagrino, N. T. Roman, and A. M. Monteiro, "Forecasting stock market index daily direction: A Bayesian Network approach," *Expert Syst. Appl.*, vol. 105, pp. 11–22, 2018, doi:

10.1016/j.eswa.2018.03.039.

[16] V. Turchenko, P. Beraldi, F. De Simone, and L. Grandinetti, “Short-term stock price prediction using MLP in moving simulation mode,” *Proc. 6th IEEE Int. Conf. Intell. Data Acquis. Adv. Comput. Syst. Technol. Appl. IDAACS’2011*, vol. 2, no. September, pp. 666–671, 2011, doi: 10.1109/IDAACS.2011.6072853.

[17] C. Y. Yeh, C. W. Huang, and S. J. Lee, “A multiple-kernel support vector regression approach for stock market price forecasting,” *Expert Syst. Appl.*, vol. 38, no. 3, pp. 2177–2186, 2011, doi: 10.1016/j.eswa.2010.08.004.

[18] A. Moghar and M. Hamiche, “Stock Market Prediction Using LSTM Recurrent Neural Network,” *Procedia Comput. Sci.*, vol. 170, pp. 1168–1173, 2020, doi: 10.1016/j.procs.2020.03.049.

[19] S. Carta, A. Ferreira, A. S. Podda, D. Reforgiato Recupero, and A. Sanna, “Multi-DQN: An ensemble of Deep Q-learning agents for stock market forecasting,” *Expert Syst. Appl.*, vol. 164, no. July 2020, p. 113820, 2021, doi: 10.1016/j.eswa.2020.113820.

[20] C. J. Hutto and E. Gilbert, “VADER: A parsimonious rule-based model for sentiment analysis of social media text,” *Proc. 8th Int. Conf. Weblogs Soc. Media, ICWSM 2014*, pp. 216–225, 2014.

[21] E. Loper and S. Bird, “NLTK: The Natural Language Toolkit,” 2002, doi: 10.3115/1225403.1225421.

[22] R. Bose, P. S. Aithal, and S. Roy, “Sentiment analysis on the basis of tweeter comments of application of drugs by customary language toolkit and textblob opinions of distinct countries,” *Int. J. Emerg. Trends Eng. Res.*, vol. 8, no. 7, pp. 3684–3696, 2020, doi: 10.30534/ijeter/2020/129872020.

[23] A. Akbik, T. Bergmann, D. Blythe, K. Rasul, S. Schweter, and R. Vollgraf, “FLAIR: An easy-to-use framework for state-of-the-art NLP,” *NAACL HLT 2019 - 2019 Conf. North Am. Chapter Assoc. Comput. Linguist. Hum. Lang. Technol. - Proc. Demonstr. Sess.*, pp. 54–59, 2019.

[24] A. Bhardwaj, Y. Narayan, Vanraj, Pawan, and M. Dutta, “Sentiment Analysis for Indian Stock Market Prediction Using Sensex and Nifty,” *Procedia Comput. Sci.*, vol. 70, pp. 85–91, 2015, doi: 10.1016/j.procs.2015.10.043.

[25] D. E. Rapach, J. K. Strauss, and G. Zhou, “International stock return predictability: What is the role of the united states?,” *J. Finance*, vol. 68, no. 4, pp. 1633–1662, 2013, doi: 10.1111/jofi.12041.

[26] A. Alsaeedi and M. Z. Khan, “A study on sentiment analysis techniques of Twitter data,” *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 2, pp. 361–374, 2019, doi: 10.14569/ijacsa.2019.0100248.

[27] W. Khan, U. Malik, M. A. Ghazanfar, M. A. Azam, K. H. Alyoubi, and A. S. Alfakeeh, “Predicting stock market trends using machine learning algorithms via public sentiment and political situation analysis,” *Soft Comput.*, vol. 24, no. 15, pp. 11019–11043, 2020, doi: 10.1007/s00500-019-04347-y.

[28] M. N. M. Ibrahim and M. Z. M. Yusoff, “Twitter sentiment classification using Naive Bayes based on trainer perception,” *2015 IEEE Conf. e-Learning, e-Management e-Services, IC3e 2015*, pp. 187–189, 2016, doi: 10.1109/IC3e.2015.7403510.

[29] R. Joshi and R. Tekchandani, “Comparative analysis of twitter data using supervised classifiers,” *Proc. Int. Conf. Inven. Comput. Technol. ICICT 2016*, vol. 2016, 2016, doi: 10.1109/INVENTIVE.2016.7830089.

[30] M. Qasem, R. Thulasiram, and P. Thulasiram, “Twitter sentiment classification using machine learning techniques for stock markets,” *2015 Int. Conf. Adv. Comput. Commun. Informatics, ICACCI 2015*, pp. 834–840, 2015, doi: 10.1109/ICACCI.2015.7275714.

[31] M. Dang and D. Duong, “Improvement methods for stock market prediction using financial news articles,” *NICS 2016 - Proc. 2016 3rd Natl. Found. Sci. Technol. Dev. Conf. Inf. Comput. Sci.*, pp. 125–129, 2016, doi: 10.1109/NICS.2016.7725636.

[32] M. Tirea and V. Negru, "Text Mining News System - Quantifying Certain Phenomena Effect on the Stock Market Behavior," *Proc. - 17th Int. Symp. Symb. Numer. Algorithms Sci. Comput. SYNASC 2015*, pp. 391–398, 2016, doi: 10.1109/SYNASC.2015.65.

[33] S. Biswas, P. Das, R. Bose, and S. Roy, "Examining the Effects of Pandemics on Stock Market Trends through Sentiment Analysis," *J. Xidian Univ.*, vol. 14, no. 6, 2020, doi: 10.37896/jxu14.6/138.

[34] M. M. Mostafa, "Forecasting stock exchange movements using neural networks: Empirical evidence from Kuwait," *Expert Syst. Appl.*, vol. 37, no. 9, pp. 6302–6309, 2010, doi: 10.1016/j.eswa.2010.02.091.

[35] H. Liu and Z. Long, "An improved deep learning model for predicting stock market price time series," *Digit. Signal Process. A Rev. J.*, vol. 102, p. 102741, 2020, doi: 10.1016/j.dsp.2020.102741.

[36] J. Long, Z. Chen, W. He, T. Wu, and J. Ren, "An integrated framework of deep learning and knowledge graph for prediction of stock price trend: An application in Chinese stock exchange market," *Appl. Soft Comput. J.*, vol. 91, p. 106205, 2020, doi: 10.1016/j.asoc.2020.106205.

[37] I. K. Nti, A. F. Adekoya, and B. A. Weyori, "Predicting Stock Market Price Movement Using Sentiment Analysis: Evidence From Ghana," *Appl. Comput. Syst.*, vol. 25, no. 1, pp. 33–42, 2020, doi: 10.2478/acss-2020-0004.

[38] R. Pimprikar, S. Ramachandra, and K. Senthilkuma, "Use of Machine Learning Algorithms and Twitter Sentiment Analysis for Stock Market Prediction," *Int. J. Pure Appl. Math.*, vol. 115, no. 6, pp. 521–526, 2017.

[39] S. Mohan, S. Mullapudi, S. Sammeta, P. Vijayvergia, and D. C. Anastasiu, "Stock price prediction using news sentiment analysis," *Proc. - 5th IEEE Int. Conf. Big Data Serv. Appl. BigDataService 2019, Work. Big Data Water Resour. Environ. Hydraul. Eng. Work. Medical, Heal. Using Big Data Technol.*, pp. 205–208, 2019, doi: 10.1109/BigDataService.2019.00035.

[40] D. Shah, H. Isah, and F. Zulkernine, "Predicting the Effects of News Sentiments on the Stock Market," *Proc. - 2018 IEEE Int. Conf. Big Data, Big Data 2018*, pp. 4705–4708, 2019, doi: 10.1109/BigData.2018.8621884.

[41] A. de Myttenaere, B. Golden, B. Le Grand, and F. Rossi, "Mean Absolute Percentage Error for regression models," *Neurocomputing*, vol. 192, pp. 38–48, 2016, doi: 10.1016/j.neucom.2015.12.114.