A Methodology for Stock Movement Prediction Using Sentiment Analysis on Twitter and StockTwits Data

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***Abstract*—Application of Machine Learning (ML) and sentiment analysis on data from microblogging services has become a common approach for stock market prediction. In this paper, we propose a methodology using sentiment analysis on Twitter and StockTwits data for Stock movement prediction. The methodology was evaluated by analyzing stock movement and sentiment data. We present a case study focusing on Microsoft stock. We collected tweets from Twitter and StockTwits along with financial data extracted from Finance Yahoo. Sentiment analysis was applied on tweets, and two ML models namely SVM and Logistic Regression were implemented. Best results were achieved when using tweets from Twitter with VADER and SVM. Top F-score was 76.3% and top Area Under Curve (AUC) was 67%. SVM also achieves the greatest accuracy equal to 65.8%, when using StockTwits with TextBlob on this imbalanced data set.**

Keywords--**Sentiment Analysis, Twitter, StockTwits, microblogging, Stock Market Prediction, Machine Learning, Data Mining, Classification.**

I. INTRODUCTION

Stock markets have become an essential part of the economy as it facilitates investments and capital gain [1]. A stock market is a network of economic transactions where activities of buying or selling shares take place. An equity or share market mirrors the ownership claims on businesses. This may include shares, which emanate from public stock exchange or from individual trade, for example shares of private companies sold to investors. Trading in stock markets is defined as an activity of transferring money from small individual investors to large trader investors, including banks, companies etc. However, stock market investment is characterized as a high risk activity because unpredictable behavior is observed [2].

Stock market prediction could be paramount for the investors if performed successfully. The efficient prediction of stock markets may offer investors a helpful guidance in order to make appropriate decisions whether to buy or sell shares [2]. The definition of stock market prediction is the act of trying to identify the stock's future value [3].

For many years, several methods for predicting stock market have been introduced. They can be classified into four categories. The first one is fundamental analysis, based on published financial statements. The second one is technical analysis with predictions achieved using historical data and prices. The third one involves Machine Learning (ML) and Data Mining methods applied to huge amounts of data derived from multiple sources. The last one is sentiment analysis with predictions based on published news, articles, or blogs [3]. The combination of the last two categories is much newer than the other two, and research shows it has a significant effect on making the appropriate decisions whether to buy or sell a stock [4].

This work proposes a methodology for using ML techniques and sentiment analysis to predict stock movements. Sentiment analysis is achieved using available information from microblogging platforms, such as Twitter and Stocktwits, as they provide important insights into people's emotions. A popular theory hypothesizes that when public sentiment for a company is positive, then the stock prices tend to rise and vice a versa [5]. However, when taking into consideration other economic factors, this theory is not always confirmed.

In this paper we focus, as a case study on Microsoft, thus we utilize and analyze Microsoft's stock movements using financial and sentiment data. 90.000 tweets were collected from Twitter and 7.440 tweets from StockTwits from 16-07-2020 to 31-10-2020. Financial data were also extracted from Finance Yahoo during the same period. Tweet sentiment analysis was conducted using TextBlob and Valence Aware Dictionary and sEntiment Reasoner (VADER). We also implemented two ML models, namely SVM and Logistic Regression. Results indicate that when using tweets from Twitter with VADER, SVM gives the highest F-score equal to 76.3% and Area Under Curve (AUC) equal to 67%.

The remaining of the paper is structured as follows: Section II provides context and reviews the state of the art. Section III details the proposed methodology, while section IV elaborates on result evaluation. The paper concludes in section V with directions for further work.

II. BACKGROUND

Social media, reflect public sentiment about current affairs and impact daily life more than ever [6]. Many studies used Twitter or StockTwits data to apply sentiment analysis in the field of stock market strategy. Related work is defined in this section.

A. Classification algorithms

Classification algorithms are predictive calculations which recognize, understand and map data into categories [7]. We present here the best-known ones.

KNN (K-nearest Neighbours) is a non – parametric, lazy algorithm. KNN measures the difference or the similarity between two instances x and y by computing the distance with the most popular distance function, the Euclidean distance d(x, y). KNN calculates the minimum distance from the query point instance to the training data set, with a view to determining the K – nearest neighbors [8].

SVM (Support Vector Machine) is a classifier which solves binary problems by searching an optimal hyperplane that can separate the points with the largest margin in the high-dimensional space. If points are linearly separable, then there exists a hyperplane that categorizes the two classes. The goal of support vector classification is to 'fit' a good separating hyperplane between the two outcomes, by finding the hyperplane that maximizes the margin between the classes [9].

Logistic Regression is a classification algorithm used for estimating the probability that an observation belongs to one of the two possible classes, 1 or 0. Logistic Regression applies a complex function named sigmoid, which maps the predicted values with the respective probabilities. The output of the function is 0 or 1 [10].

Decision Tree is a classifier which predicts the class of the target variable by using decision rules. The application of "divide and conquer" method is useful for generating a tree [11]. The variable used for the root node is selected based on its high p-value and the tree is divided into sub-trees. The sub trees are further split by following the same procedure until the leaf node is reached. After the creation of the tree, decision rules can be extracted [12].

Random Forest is an ensemble learning algorithm which consists of multiple decision trees constructed randomly. Random forest searches for the best feature among a random subset of features with a view to applying it as a splitting criterion for each node. Random Forest eliminates the problem of overfitting and achieves greater prediction accuracy than traditional Decision Trees [13].

Multilayer Perceptron (MLP) is a supervised learning technique and a deep artificial neural network. MLP consists of multiple layers of input nodes, which are linked as a direct graph between the input and output layers. The input layer receives the signal, and the output layer makes the prediction. The goal is to model the correlation between the input and output [14].

For our methodology, SVM and Logistic Regression were implemented.

B. Performance evaluation metrics

Different evaluation metrics are used in order to assess behaviours of classification algorithms. In this paper, we use accuracy, F-score and AUC to evaluate the algorithms. They are defined below [15].

Accuracy is the ratio of true positives and true negatives divided by the total instances. It presents the instances that have been correctly classified.

Precision is the ratio of true positives to all the predicted positive cases.

Recall is the ratio of true positives to all the actual positive cases.

F-score is a measure that computes the harmonic mean of precision and recall. This score takes both false positives and false negatives into account.

AUC is a measure that a classifier is capable of distinguishing between the positive and negative classes.

C. Sentiment Analysis Applications

Sentiment analysis on social media data has played a significant role for prediction in various domains. It is the process of identifying opinions expressed in texts in order to indicate whether they are positive (favorable) or negative (unfavorable) towards the subject. Some of its benefits include the advance of marketing strategies, improvement of customer service, increase of sales revenue, detection of unfavorable rumors for risk management etc. [16]. Here we present several such popular fields, and then focus on stock market prediction specifics.

Oikonomou et al. focused on election result predictions. They created a model to forecast the results of the 2016 US presidential elections. The authors predicted correctly who would win the elections in the three primary states of US including Florida, Ohio and N. Carolina [17]. They extracted data from Twitter and sentiment analysis was performed by TextBlob and Naïve Bayes. Beleveslis et al. conducted a survey on the sentiment of Greek tweeter users related to the 2019 European Parliament Elections. The authors concluded that Random Forest was more capable of predicting neutral and negative tweets with an F-score equal to 83% and 73% respectively. However, the algorithm had a difficulty in predicting positive tweets with an F-score equal to 34% [18].

Tsiara et al. [19] aimed to predict the chart position for songs. In particular, the authors collected chart data including titles, artist names and rankings and Twitter data which are related to the top 10 songs and artists for each week. They gathered more than one million tweets and sentiment analysis was performed by VADER. Their results indicated that there is a moderate correlation between the title of a song referred to Twitter posts and the success of the song on Billboard Hot 100 Chart for the following week. However, there was a weak correlation between tweets that provide the number of mentions of an artist and the future performance of a song. In addition, with regards to the scoring algorithms, the authors achieved an accuracy of 80% for predicting the top 10 songs and F-scores of 88.1% and 38.5% for predicting hit and non-hit songs, respectively.

Koukaras et al. [20] conducted a literature review on using social media data in healthcare. Thanks to the existence of social media data, people can detect, mitigate, and predict diseases, virus outbreaks, vaccination decisions etc. The contribution of the sentiment analysis of social media data is very important as deaths are prevented and healthcare costs are decreased etc.

Rousidis et al. [21] reviewed trending domains of social media prediction using recent literature. The authors analyzed several fields, which have been categorized into three groups: Finance, Marketing and Sociopolitical. The finance category focuses on stock market or product pricing prediction. The marketing group includes the prediction of trends, behavior etc. and the sociopolitical one includes the prediction of elections, natural phenomena etc. Their conclusions show that not all model predictions are highly accurate and as accuracy seems to vary across various domains. In particular, in 53.1% of the examined domains a valid prediction was achieved, in 18.8% it was not, and in the remaining there was a plausible valid prediction. In addition, their survey demonstrated that more than 75% of researchers use Twitter data and more than 50% use Regression algorithms for making predictions.

D. Twitter Applications

Pagolu et al. [22] implemented twitter sentiment analysis and ML techniques to analyse the correlation between a company's stock market fluctuations and the sentiment of tweet texts. They extracted tweets, as well as stock opening and closing prices for Microsoft from the Yahoo Finance website during the period from 31-08-2015 to 25-08-2016. Models were built using Logistic Regression and LibSVM algorithms with 69.01% and 71.82% accuracy, respectively. Results showed that performance with a large dataset was good, and there was also a good correlation between stock market fluctuations and tweet expressed public sentiment.

Kordonis et al. [23] conducted a survey whether public sentiment is correlated with stock market values for the 16 most popular tech companies, such as Microsoft, Amazon, Apple Blackberry etc., employing SVM and Naïve Bayes algorithms for analyzing public's sentiment. Using 7-fold cross validation, they accomplished 80.6% accuracy with Naïve Bayes and 79.3% accuracy with SVM on predicting the sentiment. However, they applied SVM for stock market prediction. The results showed that accuracy was equal to 87%. In addition, the prediction error was assessed to be under 10%, in the presence of noise, for all the tech

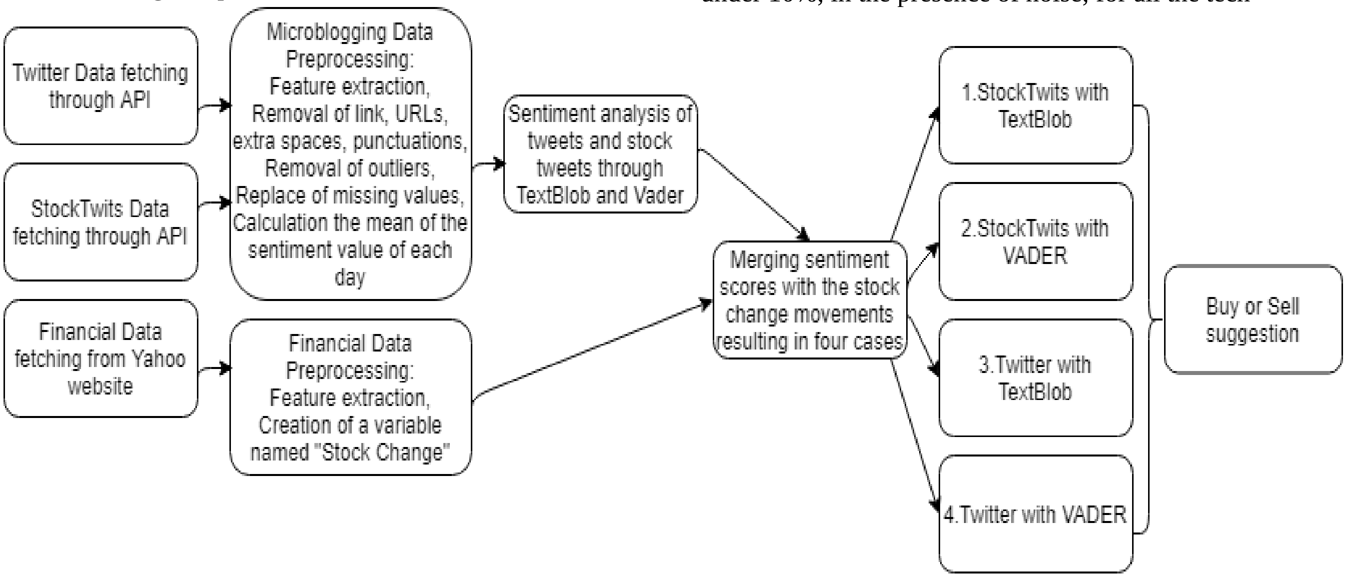

Figure 1: Flowchart for the proposed methodology

companies. In general, the average prediction error for all the tech companies was 1.67%, which demonstrates a good performance.

Hamed et al. [24] were the first to investigate the correlation between Saudi tweets and the Saudi market index. The tweets data were selected from Mubasher using an API. Mubasher is a stock analysis software provider in the Gulf region. In total, they extracted 3335 tweets over 53 days, from 17/03/2015 to 10/05/2015. Also, they mined the closing prices of the TASI index. Sentiment analysis was performed by using ML algorithms including Naïve Bayes, KNN and SVM. The model was evaluated by computing accuracy. The accuracy of SVM was equal to 96.6% and of KNN was 96.45%. The results indicated that when the negative sentiment was increasing, then the positive sentiment was falling and the TASI index was also dropping. The authors concluded that there is a good correlation between sentiment and the TASI index.

E. StockTwits Applications

Gupta et al. [25] examined the causative relation between the sentiment from StockTwits data and stock price movements for five companies including Apple, Amazon, General Electric, Microsoft, and Target. They collected stock and StockTwits data from 01-01-2019 to 30-09-2019. Sentiment analysis was performed using three classifiers (Naïve Bayes, SVM and Logistic Regression) and five featurization methods (bag of words, bigram, trigram, TF-IDF, and LSA). To forecast the stock price movements for a day, the model was built with the help of both financial data and aggregated sentiments from the previous five days. The resulted accuracy ranged between 62.3% and 65.6%, with Apple and Amazon presenting the highest performance.

Batra et al. [26] focused on Apple's stock prediction using the combination of stocktwits and financial data extracted from 2010 to 2017. They applied SVM to forecast public sentiment and predict if a person will buy or sell a stock. The attributes selected for the model were three: date, stock price decision and sentiment. The training and test models achieved 75.22% and 76.68% accuracy, respectively. According to the authors, the results seem to be good, but can be improved by increasing the size of the dataset.

III. METHODOLOGY

In this paper, we propose a methodology using sentiment analysis on Twitter and StockTwits data for stock movement prediction, comprising several steps. First, we extract tweets from Twitter and stock tweets from StockTwits, using APIs. We apply sentiment analysis on tweets, using tools, such as

TextBlob and VADER. VADER is a lexicon and rule-based sentiment analysis tool for social media data. VADER does not only return positive, neutral, or negative values, but also assesses how positive or negative a sentiment is [27]. On the other hand, TextBlob is a sentiment analysis library returning a sentiment score for each tweet [28].

Next, we extract financial data from Yahoo finance. We then merge stock price movements, the stock change variable, with the sentiment scores, and develop the stock market prediction model using six classifiers. To test the proposed model, we split the data into training and test set; 80% for training the model and 20% for testing it.

The proposed methodology for predicting stock movement is depicted in Fig. 1 and detailed in the following subsection.

A. Data Collection

1) Twitter Data

A developer account was created to connect with Twitter's API. For the case study on Microsoft, we wanted to explore public opinion about the company's stock, as well as their products and services. We collected and filtered Tweets in English using keywords, such as #Microsoft, #MSFT, #Microsoft365. From each tweet we extracted the keyword, user id, user account, date of creation and tweet text, and stored these in a database. In total, 90.000 tweets were collected from Twitter during the period from 16-07-2020 to 31-10-2020.

2) StockTwits Data

The extraction of stock tweets is based on language, time, and company ticker through the search API. Importing the library named requests, the server returns a JSON object of tweets. The object contains the user account, the text of tweets and the date of creation. Tweet extraction is based on the company ticker, like $MSFT. Stock tweets were also stored in the database. In total, 7.440 tweets were collected from StockTwits during the period from 16-07-2020 to 31-10-2020.

3) Financial Data

Microsoft's historical data were extracted from Yahoo! Finance, containing vast amounts of international market data, up-to-date news, stock quotes or portfolio resources [29]. The collected attributes were closing and opening price, low and high price, volume and adjusted price. In total, 77 reporting dates were collected from Yahoo during the period from 16-07-2020 to 31-10-2020.

B. Sentiment Analysis

1) VADER

We used the polarity_scores() method from the "SentimentIntensityAnalyzer" library to obtain the polarity for each text. This method returns four scores: negative, positive, neutral and the compound score, the sum of all lexicon ratings, negative, positive and neutral ones. When using data from StockTwits, most tweets were found to be neutral. Specifically, 46.7% of tweets were neutral, 43.3% positive and 10.0% negative. This means that most users are neutral to positive with regards to buying or selling Microsoft stock. However, when using data from Twitter, most tweets were positive. Specifically, 48.0% of tweets were positive, 28.0% neutral and 24.0% negative.

2) TextBlob

We also classified tweets into positive, neutral and negative using the "TextBlob" library. 53.3% of tweets from StockTwits, were found to be neutral, 40.0% positive and 6.7% negative. Similarly, 48.0% of tweets from Twitter were also neutral, 36.0% positive and 16.0% negative.

C. Pre-processing

1) Symbol Removal

Before conducting sentiment analysis, we removed certain symbols, such as @, $, URLs, extra spaces, and punctuations because they do not add value to the sentiment analysis.

2) Outlier Removal

The dataset contains outliers, which were removed. The outliers threat the validity of the model because they constitute an important part of the initial dataset, as shown in Table 1.

TABLE 1: OUTLIER DISTRIBUTION

Dataset	Outliers
Twitter with VADER	19.7%
Twitter with TextBlob	9.6%
StockTwits with VADER	27.1%
StockTwits with TextBlob	27.3%

Extremely positive or negative data were removed to mitigate any bias. In this paper, we used as flooring the 10th percentile for low values and as capping the 90th percentile for the high values.

3) Replacing missing values

Collecting tweets for all the days was not possible because Twitter has a 7-day limit, which means that no tweets will be found for a date beyond one week old. Thus, the missing sentiment was replaced with the mean value. In addition, stock data were missing over weekends or whenever the stock market is off. So, in order to replace the missing values, we used a function which linearly interpolates between known data with a view to obtaining the unknown values. Linear interpolation is a method for estimating unknown values that appear to be between the known values [30].

4) Feature selection

For the needs of this paper, we used as input the following attributes including low and high price, volume and adjusted price and we also created two additional features. The mean sentiment score of each day, which represents one of the inputs of the model and the stock change movement, which represents the target variable. In particular, we calculated the mean of the sentiment value for each day, because when downloading tweets, we gathered multiple sentiment values for one day. However, for our purposes, we only need one sentiment value, which constitutes the sentiment for each day. We also created a new variable called "Stock Change", in order to decide whether the stock price increases or decreases. To make this decision, the close price was subtracted from the open price and divided by the open price, as shown in (1).

$$\text{Stock Change} = \frac{Close - Open}{Open} \quad (1)$$

If the result of the stock change is greater than zero it means that the stock change is positive, therefore the stock price decreases and the person can buy Microsoft's securities. We indicate this result as equal to 1. Otherwise, if the result of the stock change is negative, the stock price increases and the person can sell the stock in order to earn profit. This result is indicated as equal to -1.

IV. RESULTS AND EVALUATION

In this study, a binary classification was implemented. The input variables include the sentiment value, low and high price, volume, and adjusted price. However, the target variable is the stock change, which has two distinct values: -1 and 1. It contains two values which represent the status of selling or buying the stock, respectively. To evaluate the proposed model, three metrics were used: accuracy, F-score and Area Under Curve (AUC). The F-score is a measure of a model's accuracy and demonstrates the predictive power, how correct our predictions are [31]. AUC is the area under the curve of plotting true positive rate and false positive rate [32]. It describes the discriminatory power, how capable is the model to distinguish if the stock price will rise or fall. This section presents results using VADER and TextBlob as Twitter and StockTwits sentiment analysis tools.

Table 2 shows F-scores ranging from 70.1% to 76.3%. The best performance, 76.3%, is achieved by SVM, Logistic Regression being second best with 70.1%. However, AUC fluctuates from 67% to 63.2%. SVM achieves the greatest discriminatory power with 67%, and the second best is Logistic Regression with 63.2%.

TABLE 2: ACCURACY, F-SCORES & AUC USING TWITTER WITH VADER

Algorithm	Accuracy	F-score	AUC
SVM	50.1%	**76.3%**	**67%**
Logistic Regression	50.6%	70.1%	63.2%

In Table 3, the greatest F-score is 75% from SVM again. However, Logistic Regression presents a F-score equal to 54.1%. The AUC is equal to 50% for both algorithms.

TABLE 3: ACCURACY, F-SCORES & AUC USING TWITTER WITH TEXTBLOB

Algorithm	Accuracy	F-score	AUC
SVM	48.2%	**75%**	50%
Logistic Regression	46.6%	54.1%	50%

In Table 4, F-scores is equal to 68% for both SVM and Logistic Regression, while AUC is equal to 55% and 54.7% respectively.

TABLE 4: ACCURACY, F-SCORES & AUC USING STOCKTWITS WITH VADER

Algorithm	Accuracy	F-score	AUC
SVM	**57.6%**	**68%**	**55%**
Logistic Regression	54.5%	**68%**	54.7%

In Table 5, SVM is the model with the greatest F-score 68%, when using StockTwits with TextBlob, with AUC equal to 53.3%. Similarly, Logistic Regression demonstrated good performance with F-score equal to 59.9% and AUC equal to 44.6%.

TABLE 5: ACCURACY, F-SCORES & AUC USING STOCKTWITS WITH TEXTBLOB

Algorithm	Accuracy	F-score	AUC
SVM	**65.8%**	**68%**	**53.3%**
Logistic Regression	56.9%	59.7%	44.6%

Best accuracy at 65.8% was achieved when using StockTwits with TextBlob (shown in Table 5). It appears rather low in comparison to F-score and AUC, as well as results reported in the literature. This was expected and is attributed to a class imbalance issue observed in the data, as it is depicted in Fig. 2-5. In the four cases, the number of the buying status is greater than the selling, which means that most people tend to buy Microsoft stocks and few of them sell them. According to Gurav et al., F-score and AUC are the appropriate metrics for imbalanced data [33].

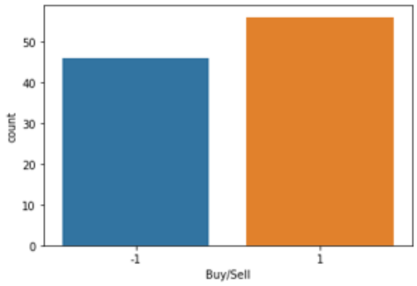

Figure 2: The distribution of stock movements using Twitter with VADER

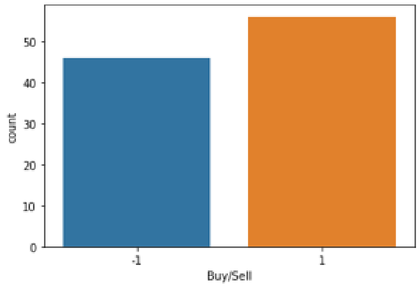

Figure 3: The distribution of stock movements using Twitter with TextBlob

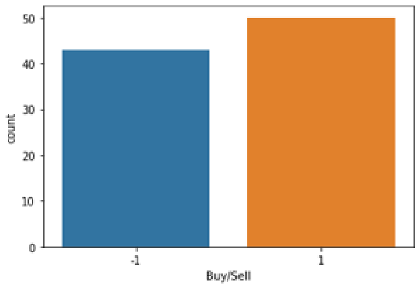

Figure 4: The distribution of stock movements using StockTwits with VADER

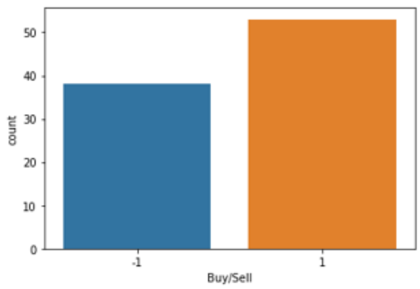

Figure 5: The distribution of stock movements using StockTwits with TextBlob

The overall average accuracy was 53.8%. When using Twitter data average accuracy was 48.9% and 58.7% when using StockTwits.

Indeed F-score and AUC performance is very good for the domain of stock movement prediction. The best F-score was 76.3%, achieved by SVM using VADER on Twitter (Table 2). The overall average F-score was 59.62%. When using Twitter data average F-score was 68.9% and 65.9% when using StockTwits.

The best AUC was 67% using SVM using Vader on Twitter (Table 2). The overall average AUC was 54.7%. When using Twitter data average AUC was 57.6% and 51.9% when using StockTwits.

All in all, using StockTwits particularly with TextBlob favours accuracy. Using Twitter with Vader favours F-score and using Twitter particularly with Vader favours AUC.

V. CONCLUSIONS AND FUTURE WORK

A. Conlusions

In this research, we investigated the issue of stock market prediction using ML methods with sentiment analysis. We dealt with Twitter and StockTwits data in combination with financial data. The sentiment of microblogging data was extracted with the help of TextBlob and VADER. After pre-processing, we evaluated our model performance, for 4 cases, using two classification algorithms: SVM and Logistic Regression.

The evaluation of the model was performed with three metrics: accuracy, F-score, and AUC. SVM was the algorithm which produced the greatest predictive and discriminatory power. The use of Twitter data, particularly with the use of VADER as sentiment analysis tool, resulted in the best F-score and AUC. In terms of F-score, SVM demonstrated the best performance (76.3%) while in terms of AUC, it demonstrated the best discriminatory power (67%). However, the use of StockTwits in combination with TextBlob, SVM performed the highest accuracy, equal to 65.8%.

All in all, with an imbalanced data set like the one used, SVM is the best option across the board. SVM using VADER on twitter data is the best algorithm in terms of F-score and AUC. SVM using TextBlob on StockTwits is also the best in terms of accuracy.

The proposed methodology for stock market prediction combines two different real-time datasets: one from StockTwits, in which users have greater expertise knowledge in stock market, and one from Twitter, which supports a community with numerous users. In addition, the target variable was defined by taking into consideration both open and close prices of stocks. In particular, we calculated the difference between the price from the first and last transaction of a trading day. Furthermore, we dealt with an imbalanced dataset on a binary classification problem and we concluded that accuracy is not a reliable metric in this case, unlike F-score and AUC. Finally, we analyzed the sentiment of Twitter and StockTwits data utilizing two different sentiment analysis tools and we concluded that VADER is the one which favors F-score and AUC.

B. Future work

There are several aspects of this research that could be improved in the future. Our future direction focuses on collecting tweets from users who have a lot of followers, as they potentially have strong influence on stock movements. In addition, the exclusion of fake twitter accounts can be researched, as these mislead sentiment calculation. Moreover, more data and trading dates could potentially improve model performance. Furthermore, we could select features which are strongly related with the target variable to improve accuracy or aggregate all the features and then choose the most effective classifier.

Lastly, we could apply different ML algorithms, such as Naïve Bayes, for calculating the sentiment score. It might be more valid if we trained and tested our twitter data rather than using an off-the-shelf library. For example, TextBlob and VADER sometimes perceive a positive comment as negative, thus producing a wrong sentiment score. So, training and testing our data could help to improve the proposed methodology.

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