Sentiment Analysis in Financial Markets

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Abstract:- Moving ahead in this era of data, there is a lot of information, which if used in the right way, can be used in the financial domain as well, to determine the market. This prediction can lead to large profits and help in understanding the complex financial markets. Sentiment analysis is a kind of data mining technique, which can be used to process and understand the textual content to derive meaningful insights. In this paper, for the purpose of sentiment analysis, natural language processing will be used, which is the area of machine learning in the rise. The techniques will be applied here onto a large dataset from Twitter and hence, analyse the public opinions about the financial markets.

Keywords:- *Predicting finances, Natural Language Processing(NLP),Financial Markets, Analysis of Sentiments, Mining Text.*

I. INTRODUCTION

Firstly, to answer why sentiment analysis is necessary in the domain of finance, it is important to understand that the financial condition is controlled by the market, and a loss in the market eventually leads to the loss of the public and investors. Analysing the market, gives one the advantage to invest safely and reduce the chances of monetary loss to the largest extent. Such analysis helps the investors in investing smartly and prevent a collapse of the financial situation. Therefore, one of the most emerging sectors of the country is quantitative research or HFT (high frequency trading).In the early 1950s, the research in the field of Quantitative Finance was started with time series analysis, where a lot of past data with Open, High, Low, Close prices were stored, further machine learning and statistical techniques such as mean reversion, ARIMA are applied on to the dataset to predict the future prices of the stocks. To observe a better and more precise forecast, machine learning algorithms like RL (Reinforcement Learning), Gated Recurrent Network (GRU) and LSTM (Long Short-Term Memory) are used nowadays. These techniques are popular in machine learning and are known to predict the future in a more accurate way than other models or statistical methods. In these researches, the data is numerical and only deals with the technical data, but it was discovered later that besides the historical trends, the public opinions and news, which is present in the form of textual data also shapes and changes the market affectively. The news and discussions around a particular stock and the general public opinion also impact the financial markets to a great extent. Besides the technological advantage of having access to information as early as possible, the ability to process the information and take advantage of it in the financial domain is a leverage and helps gain profits and understand the market well. Hence nowadays, Algorithms are used to analyse the public opinions and determine if the news in the flow is going to impact the market positively or negatively. Text mining is used to extract features and perform sentiment analysis in order to obtain meaningful conclusions from otherwise random and unstructured data. The unstructured data in the public domain is made useful by using the data mining techniques. There is a really large amount of data, that cannot be easily processed or used to form conclusions for which Text mining and Natural Language Processing are used. Sentiment Analysis is a structured investigation of public opinion and emotions towards topics, events, individuals and companies (Liu, 2012). It has been known that decisions made by humans is impacted by the emotions and thoughts about topics, hence the best way to predict the decisions in advance is to analyse those emotions, which affect important sectors such as financial sectors. Also, it has been noted that the news in the flow can impact to a great extent the future decisions, especially in the context of financial trades, if a company is going to be at loss or profit is hugely affected by the news in the public and altogether emotions of the people about that company. Apart from the opinions of individuals about a topic, the news broadcasted by the news channels on twitter also constitutes a great information. Several algorithms for the purpose of sentiment analysis have been proposed, even in the financial domain to predict the future market activities (Hagenau, Liebmann and Neumann, 2013) and to draw a correspondence between public emotions and market performances (Wisniewski and Lambe, 2013). One of the major challenges faced by the researchers in the sentiment analysis for financial data is the phrases and terms specific to the domain and its true apprehension. To deal with that, domain specific lexicons were introduced (Yekrangi and Abdolvand, 2020). This lexicon-based method is a hybrid of corpus based (Kamps et al., 2004) and dictionary based natural language processing method in order to derive useful and valid information related to financial domain. Domain specific lexicons are used and defined for the sentiment analysis. In the further of this paper, we will first review the literature, followed by the working of natural language processing, encompassing sentiment analysis through text mining and other technical details. Further, future discussions and research on this topic will end with the paper's conclusion.

II. LITERATURE REVIEW

Sentiment Analysis was first introduced in the paper Nasukawa, T. And Yi, J. ,2003, which mainly proposed it as a technique to deal with the semantic-pragmatic gap. Sentiment analysis applied to financial news articles has been the subject of numerous research. (Ding et al., 2014) found that emotions in financial news have a big effect on stock prices. These results highlight how sentiment analysis might improve market movement prediction modelling. Furthermore, algorithmic trading algorithms have used sentiment analysis in financial news(Bollen, Mao and Zeng, 2011)to investigate whether sentiment on Twitter might be used efficiently to forecast changes and trends in the financial market, demonstrating the viability of trading techniques based on sentiment. The emergence of social media platforms has given financial sentiment analysis a new angle. An analysis of the link between stock market results and Twitter sentiment by (Zhang, Fuehres and Gloor, 2011) found a strong association. Social media data is a great source of unstructured data for forecasting market trends and attitude shifts because of its volume and immediacy.Sentiment analysis has also been used in forums and online communities, in addition to Twitter. Discussions in online communities might yield useful sentiment indicators that shed light on investor opinion and possible market moves, according to research by (Audrino, Sigrist and Ballinari, 2020). Though sentiment analysis has potential, there are obstacles in the financial sector. Sentiment analysis is challenging in the financial domain because financial terminology is context-specific and ambiguous. Moreover, erroneous signals and market noise might result in poor investment choices. Context-aware sentiment analysis algorithms are one of the complex methodologies needed to address these difficulties. Researchers are investigating techniques like sentiment lexicons tailored to financial contexts to improve accuracy and exclude sentiment that isn't relevant.

Table 1: Objective/Methodology

Author	**Objective/Methodology**	**Finding /Observation**
11.	Proposed sentiment analysis	Sentiment analysis is now widely used in the natural language processing domain in order to analyse texts in various contexts.
3.	Twitter Sentimental analysis	They explored how the opinions formed on social media platforms are a major step in financial trading and affect the stock market.
9,10	Used SVM for sentiment analysis	It gave an accuracy of approximately 71.837 % , which is quite an achievement for a simple classifier-based algorithm.
1.	Used Naïve Bayes for sentiment analysis	Improved the classification accuracy to 90.3 %

III. METHODOLOGY

Sentiment analysis is a classification task; it has several methods and ways in which it can be performed. The process can include various steps such as Collecting the data or public opinion, identifying the sentiments, selecting important features, which is also called feature selection, classifying those sentiments into different categories and then further polarising those classifications, as illustrated in Figure 1.

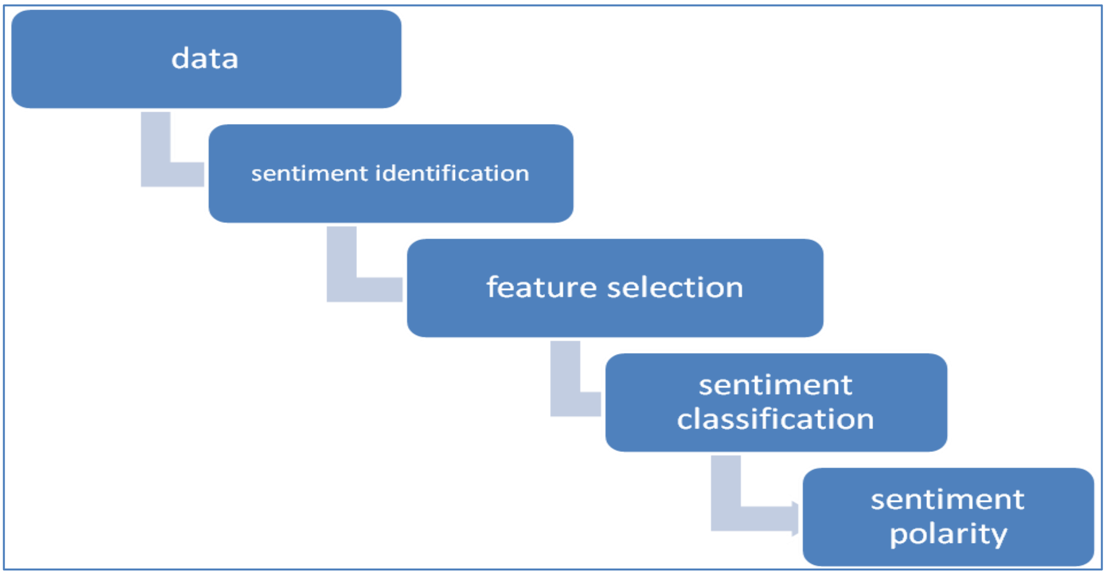

Fig. 1: Sentiment Analysis Steps and Processes(User generated figure)

Sentence-level classification, document-level classification, and aspect-level classification are the three main categories in sentiment analysis. Sentences are a form of documents, just smaller in size, hence there is little distinction between sentence-level and document-level categorization. There are majorly two major techniques in sentiment analysis, namely, the method using lexicon andanother approach using machine learning. Both supervised and unsupervised machine learning techniques are possible, with supervised learning offering many categories.Techniques based on dictionary and corpus are the two sorts of approaches that are Lexicon-based. Further statistical or semantic approaches can be used for corpus-based approaches.Firstly, we need to perform preprocessing on the textual data, procedures such as removing stop words, removing words with too high frequency or too low frequency, and performing stemming, which is defined as extracting the meaningful word out of another form ofthe same word, such as if the word is running, it is stored as run, to get the actual meaning of the word and understand the context of use.

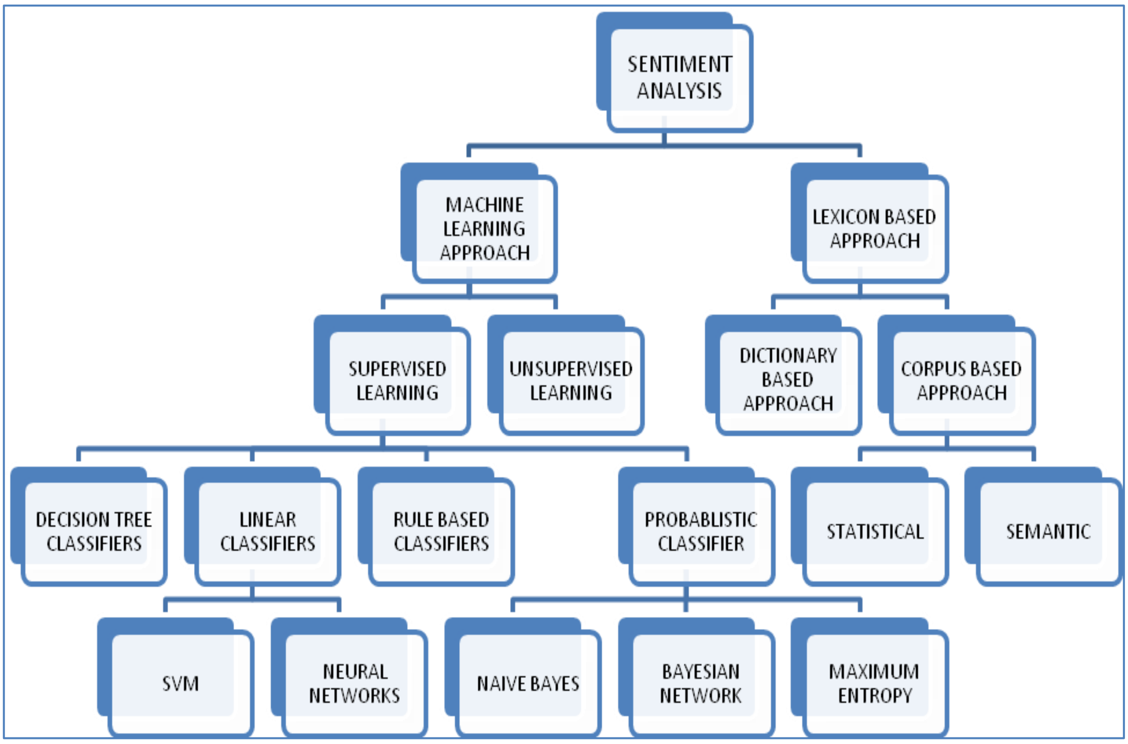

Fig. 2: Sentiment Classification Techniques(User generated figure

Following the use of these pre-processing approaches, we proceed to feature selection, utilising characteristics like:

- **Term frequency:** This characteristic is word n-grams, and the count of those words normally utilises term frequency to assign relative value to the features.
- **Part of Speech (POS):** Locate the adjectives, as they are a crucial signifier of viewpoints.
- **Opinion words and phrases:** Identifying terms that are particular to the text's context and that may be utilised to assess whether an opinion is favourable or unfavourable.
- **Negations:** When a statement contains a negation, such as "not good" being equal to "bad," the opinion orientation might be altered.

The document must first be converted into word embeddings for feature selection to be applied. Various techniques for word embedding include Global Vectors for Word Representation (GloVe), Word2Vec, and Bag of Words (BOW); any one of these methods can be used; the discussion for the right method of embedding is out of the scope of this topic. After the features are extracted, either the machine-learning approach is applied, or the lexicon-based approach is applied. The popular machine learning algorithms leverage linguistic characteristics. The technique based on lexicon makes use of a sentiment lexicon, that is a set of well-known sentiment expressions that have been precompiled and are specific to a certain situation. There are several models and methods available in the machine learning approach to apply supervised learning such as:

- Naïve Bayes classifier: This classifier, which evaluates a class's probability using the document's word distribution., is the most basic and often used one. Because this model uses Bag of Words (BOW) feature extraction, it does not take word position into account. This is not accurate enough due to the negligence of the context in which the word is being used.(A. Jabbar Alkubaisi, Kamaruddin and Husni, 2018). This method resulted into a high accuracy of 90.38 % , which enables a higher extent of correct prediction in the financial sector. A hybrid algorithm of naïve bayes was also used, for further improvement.

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Table 2: Model Accuracy parameters*

Class	Precision	Recall	F1-Score	Support
0	0.90	0.87	0.88	1081
1	0.92	0.92	0.92	1946
2	0.80	0.90	0.85	219
Average/Total	0.90	0.90	0.90	3246

*From A. Jabbar Alkubaisi, Kamaruddin and Husni, 2018.

- **Support Vector Machines:** The SVMs work on the principle of separation between the two classes and the distance between them when plotted onto a plane. Because text is sparse, text data are well-suited for SVM classification. Therefore, they can be easily separated into linearly separable categories.(Mullen and Collier, n.d.)This method when applied on financial prediction on Nigerian bank data, gave an accuracy of 71.837% (Onwuegbuche, Wafula and Mung'atu, 2019)
- **Decision Tree:** This method usually consists of dividing the data space with the leaf nodes using a condition based on which the data is divided.
- **Neural Networks:** For classifying categories, neural networks are used in general and hence can be utilised for the task of sentiment analysis as well, although the outcomes are not very different from what the support vector machines can predict.(Sohangir et al., 2018). Using Convolution Neural Networks, gave approximately 86 % accuracy , which was comparatively better than LSTMs , which turned out to be ineffective.
- Pre-trained models such as BERT, GPT, etc.

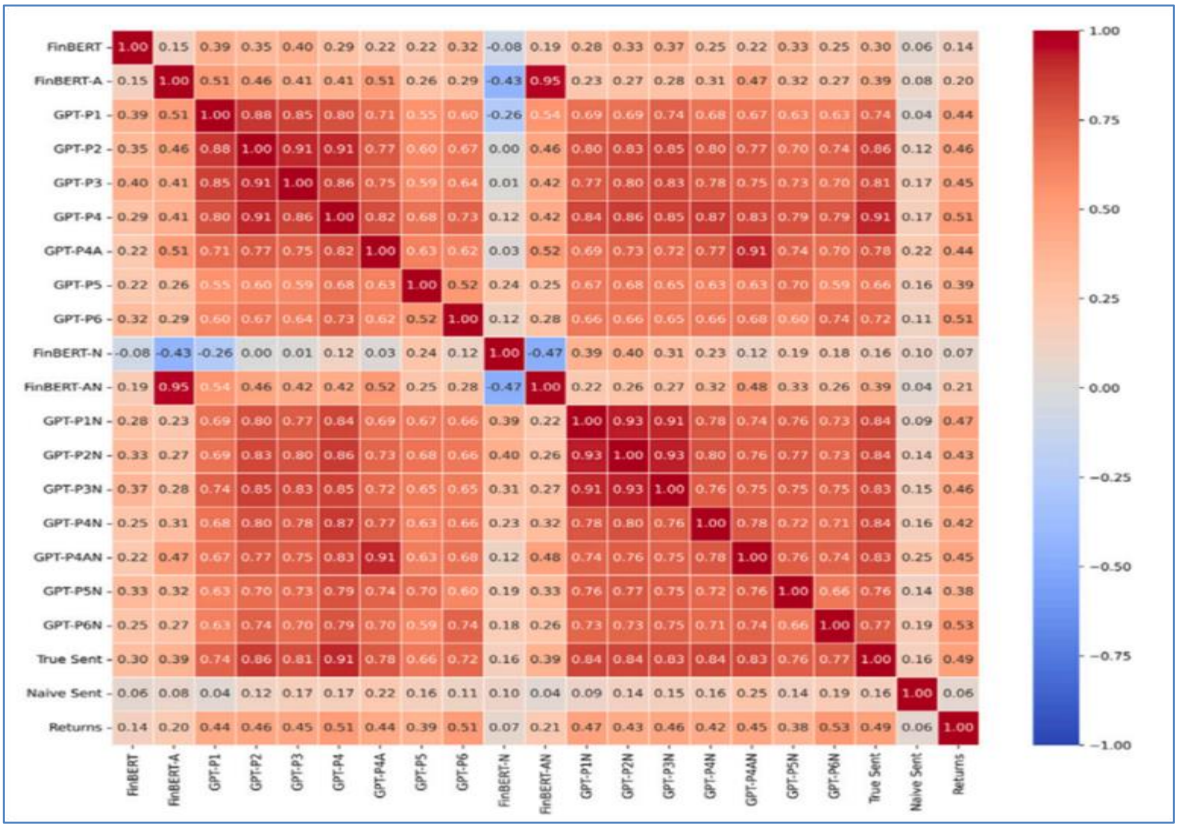

Fig. 3: Correlation matrix of predicted sentiment and market*
*from Georgios Fatouros et al. (2023)

Using models such as GPT gives a high correlation, which typically suggests that there is a high correlation present between the market values and the sentiments predicted by these models. However, it must be noted that the high correlation does not necessarily imply predictive power over future market prices. Financial market systems are complex and involve a variety of factors, which include socioeconomic conditions and other factors. analysing the sentiments present in social media about certain topics can help determine the general public opinion but sometimes can be biased or favoured.

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IV. RESULTS

From the above discussion, it is clear that various models have been tested and following results have been observed-

Table 3: Classic ML model performance *(Karanikola et al., 2023)

Classic ML models + TF-IDF

Model	Accuracy	AUC	Recall	Precision	F1	Kappa	MCC
Classic ML models							
LR	0.6974	0.8338	0.6974	0.682	0.6671	0.4375	0.4608
CatBoost	0.6846	0.8168	0.6846	0.6764	0.6582	0.4138	0.4374
SVM	0.682	0.8347	0.682	0.6598	0.6546	0.415	0.4314
Ridge	0.6666	0.7863	0.6666	0.6524	0.651	0.402	0.4108
XGBoost	0.6647	0.806	0.6647	0.6537	0.6443	0.3874	0.4031
ET	0.6578	0.7096	0.6578	0.6387	0.6424	0.3899	0.3963
GBC	0.6604	0.7937	0.6604	0.6653	0.6202	0.3484	0.3923
AdaBoost	0.6514	0.6774	0.6514	0.6609	0.6212	0.3449	0.3778
RF	0.6463	0.7702	0.6463	0.6281	0.6281	0.3626	0.372
KNN	0.6306	0.7701	0.6306	0.6278	0.6233	0.3541	0.3587
LightGBM	0.6364	0.7772	0.6364	0.6211	0.6213	0.35	0.3572
DT	0.5878	0.6645	0.5878	0.6016	0.5939	0.3103	0.3109
NB	0.5076	0.6252	0.5076	0.5639	0.5256	0.2288	0.2349
LDA	0.2429	0.3461	0.2429	0.2736	0.2521	0.0447	0.046
DC	0.5358	0.5	0.5358	0.2871	0.3739	0	0
QDA	0.2093	0.4684	0.2093	0.3587	0.2267	−0.0534	−0.0716
Ensembles							
CatBoost+LR+SVM	0.6882	0.8408	0.6882	0.67	0.6588	0.4216	0.4432
CatBoost+LR+Ridge	0.6837	0.837	0.6837	0.6638	0.6595	0.4216	0.4369
LR+XGBoost+SVM	0.6837	0.8372	0.6837	0.6647	0.6575	0.4177	0.436
CatBoost+SVM+Ridge	0.682	0.8362	0.682	0.6611	0.6581	0.4192	0.4338
CatBoost+XGBoost+SVM	0.682	0.8349	0.682	0.6655	0.6562	0.4134	0.4328
LR+XGBoost+Ridge	0.6801	0.8341	0.6801	0.6591	0.6578	0.4181	0.4312
CatBoost+LR+XGBoost	0.6809	0.8351	0.6809	0.6635	0.6543	0.4105	0.4306
CatBoost+XGBoost+Ridge	0.679	0.831	0.679	0.6605	0.6566	0.4146	0.429
LR+SVM+Ridge	0.6784	0.8338	0.6784	0.6561	0.6557	0.4155	0.4277
XGBoost+SVM+Ridge	0.6771	0.8338	0.6771	0.6562	0.6552	0.4132	0.4258

Table 4: Deep Learning Model Performance Comparisons *(Karanikola et al., 2023)

Deep learning pre-trained models' performance

Model	Accuracy	AUC	Recall	Precision	F1	Kappa	MCC
RoBERTa	0.775877	0.920793	0.775877	0.775877	0.775877	0.632183	0.634966
BERT	0.74166	0.89992	0.74166	0.74166	0.74166	0.554974	0.558077
FinalcialBERT	0.704876	–	0.704876	0.704876	0.704876	0.47108	0.486317
FinBERT (Yang & Huang)	0.65355	–	0.65355	0.65355	0.65355	0.355566	0.389141
FinBERT (Araci)	0.570573	–	0.570573	0.570573	0.570573	0.224854	0.256037

V. FUTURE RESEARCH

As the research is advancing in this domain, more and more language models are being utilised to sense the market and hence language models such as GPT(Georgios Fatouros et al., 2023) are being used, but instead of domain-specific news headlines, it will be better if unrelated news is also fed into the modelas sometimes various other factors also play a significant role in deciding the fate of stocks and trades.Apart from this, the data duration that we can analyse right now is comparatively small for a volatile domain such as finance; hence, in future studies, a longer duration of data can validate the findings and predictions.It is crucial to expand our research horizon, as with the passing of time, we are getting introduced to newer and more capable language models such as OpenAI's ChatGPT, which is trained using real-world data and relies less on synthetically generated datasets. As the research is also advancing in the domain of LLMs, future research can explore options by comparing existing and emerging models.A major issue that needs to be addressed in the future is the response time, which is large when dealing with large amounts of data. Models often face fluctuations in system loads and a memory shortage or a prolonged processing time when dealing with complex data. Further, language models can be developed that leverage their complete potential in finance as well.Hence the future research work can be explored in the domains of language models , efficient memory and processing time management as well as other advancements in the natural language processing methods.

VI. CONCLUSION

In conclusion, this paper explores all the possible ways of implementing natural language processing in analysing the sentiments in predicting the financial market movements. It first explores the sentiment anlysis , followed by analysing thesignificance of applying sentiment analysis to the financial domain, followed by the basic NLP techniques required to do so. Analysing sentiments of the market helps make smart decisions and is also attractive for investors as it prevents huge market losses and financial collapses. The literature review emphasisesthe fact that the previous research in this domain has been done mainly in the quantitative data and is now slowly progressing to analysing public opinion, as it has been realised that the unstructured data present on social media can be exploited to get useful insights about the market. Themethodologyfocuses on the various steps that are required in sentiment analysis: preprocessing techniques, feature selection methods and model exploration. After cleaning the unstructured data and transforming it into desired word embeddings, various models are to be explored, such as support vector machines and language models such as BERT, GPT, RoBERTa, etc.Further, the future scope of research in the domain has been discussed, describing how memory issues with the existing models persist and how analysing a larger amount of data can lead to better analysis and prediction as the finance industry is indeed a complex one and is affected by constantly various topics.

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