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COMPARISON OF LEXICON-BASED METHOD, MACHINE LEARNING AND CHATGPT ON SENTIMENT ANALYSIS OF BIG CAP AND SMALL CAP COMPANIES IN UNITED STATE INDEXES

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ABSTRACT

Sentiment analysis is a natural language processing (NLP) method that identifies the sentiment contained in a body of text. It has gained significant attention due to its potential applications in various domains, including finance, marketing, and public opinion monitoring. In the financial sector, sentiment analysis is essential for analyzing market trends, forecasting stock prices, and guiding investment choices. This research paper compares the performance of lexicon-based method, machine learning technique, and ChatGPT in sentiment analysis of big cap and small cap companies in United States indexes using Twitter data. The purpose of implementing ChatGPT is to identify the usefulness of this well-known tool that is currently flooding the social media scene. The results show that Random Forest achieved the highest accuracy overall with 83.6% on big cap and 78.8% on small cap. ChatGPT sentiment has an accuracy of 77.44% on big cap and 72.43% on small cap. Meanwhile the lowest performing method is the TextBlob which has an accuracy of 46.52% on big cap and 43.57% on small cap. Random Forest is able to understand the context of tweets and handle slang terms and phrases, while ChatGPT is still under development but has the potential to perform better in the future. There are many slang terms and phrases that are used in the stock market that are not included in the TextBlob dictionary. Therefore, the performance of TextBlob is the least performing method.

Keywords: *Sentiment Analysis, Random Forest, Lexicon, Textblob, Machine Learning, Chatgpt*

1. INTRODUCTION

Natural language processing (NLP) method called sentiment analysis, also referred to as opinion mining, identifies the sentiment contained in a body of text aimed to understand and extract sentiments, opinions, and emotions expressed in textual data [1]. With the rapid growth of digital content and the widespread use of social media platforms, sentiment analysis has gained significant attention due to its potential applications in various domains, including finance, marketing, and public opinion monitoring. Sentiment analysis is essential for analyzing market trends, forecasting stock prices, and guiding investment choices in the financial sector [2]. Investors and financial experts are particularly interested in understanding the attitude surrounding big cap and small cap companies that are listed on United States indexes. Small cap firms have smaller market capitalizations and frequently represent specialized or emerging industries, whereas big cap companies are those with a higher market capitalization and typically hold more established market positions [3].

Moreover, social media platforms like Twitter, Facebook and Instagram have become an abundant source of real-time data and opinions [4]. Analyzing sentiment from Twitter data can provide valuable insights into public perception, trends, and investor sentiment towards big cap and small cap companies. Collecting data using the Twitter API enables the acquisition of a rich dataset comprising tweets related to these companies, facilitating a comprehensive sentiment analysis.

Traditionally, lexicon-based methods have been utilized, which rely on pre-defined sentiment dictionaries or word lists to determine the sentiment of a given text [5]. While these methods have shown some success, they often struggle with handling context-specific and nuanced sentiments, leading to limitations in their accuracy. Furthermore, machine learning approaches have gained popularity in sentiment analysis due to their ability to learn patterns and relationships from data [6]. These methods leverage various classification algorithms to automatically classify sentiments based on labeled training data. Although machine learning techniques have achieved promising results, they require substantial amounts of labeled training data and feature engineering, which can be time-consuming and resource-intensive [7]. To address the limitations of existing approaches, we propose leveraging ChatGPT, an advanced language model based on GPT-3.5 architecture developed by OpenAI. ChatGPT has been trained on a vast corpus of text from diverse sources, providing it with a comprehensive understanding of language patterns and nuances [8]. By employing ChatGPT for sentiment analysis of big cap and small cap companies, we aim to explore the potential advantages of utilizing a language model that can capture complex contextual information and generate human-like responses. The problem lies in comparing the performance and effectiveness of lexicon-based methods, machine learning algorithms and ChatGPT. The objective is to identify the most accurate and reliable method for sentiment analysis in the financial domain, considering the complexities and nuances associated with sentiments expressed towards different types of companies.

Our methodology entails gathering a sizable dataset of textual information about big cap and small cap companies in United States indexes from tweets that will be collected using Twitter API. In terms of accuracy, efficiency, and their capacity to detect subtle emotions, lexicon-based approach, machine learning algorithm, and ChatGPT will all be put to the test. Precision, recall, F1-score, and sentiment classification accuracy will be among the evaluation metrics.

This research paper aims to compare the performance of lexicon-based methods, machine learning techniques, and ChatGPT in sentiment analysis of big cap and small cap companies in United States indexes using Twitter data. The justification for utilizing the Twitter API and the proposed methodology is rooted in the availability of real-time data and the opportunity to capture the sentiment of individuals expressed on a popular social media platform [9]. By comparing these three distinct approaches, we can identify the most suitable and effective method for sentiment analysis of big cap and small cap companies in United States indexes, enabling investors and financial analysts to make informed decisions based on sentiment trends in real-time.

The rest of the paper is organized as follows: Section 2 will be explaining about the background study of sentiment analysis. We will explain about the techniques and the performance of the techniques used by the authors. In section 3, we explain the workflow of our research by describing the methodology of the work. In section 4, we will discuss the results that we achieve from the techniques used. In section 5, we give an explanation about the experience performing sentiment analysis on tweets to provide the conclusion and future work.

2. BACKGROUND STUDY

This section of the paper reviews a number of research papers that have works similar to ours. These studies claim that prior to executing the classification, data preprocessing operations such as stopword removal, stemming, and tokenization are required. Data preprocessing is a crucial step in any data analysis task, including sentiment analysis. It involves preparing and transforming raw data into a format that is suitable for analysis, ensuring data quality, consistency, and compatibility with the chosen methods and models.

Natt Leelawat et al. [6] conducted a study on sentiment analysis of tourism in Thailand during the COVID-19 pandemic. Machine learning algorithms such as Classification and Regression Tree (CART), which is used to generate a decision tree, Random Forest (RF) and Support Vector Machine (SVM) are optimized with English-language tweets expressing sentiments about tourist attractions, events, festivals, and experiences from July to December 2020. With an F1 score of 0.771, the support vector machine produced the maximum accuracy (up to 77.4%), which was deemed an acceptable percentage. Random forest came in second with an accuracy of 70.8%, while CART had the lowest accuracy at 63.9%. The results of this study show that machine learning algorithms are capable of accurately predicting the goals and feelings of the source material. The word choice in each class, after the text has been divided into sentiment and intention classes, can aid in determining the sentiments and travel-related intentions of visitors. Since the use of Random Forest is achieving a high accuracy for sentiment analysis on tweets, we could utilize it in a stock market domain.

Veny Amilia Fitri et al. [10] performed sentiment analysis of social media Twitter with case of anti-LGBT campaign in Indonesia using multiple machine learning models such as Naive Bayes, Decision Tree and Random Forest. She used the Anti-LGBT campaign as a case study for sentiment analysis because Indonesians have been discussing it a lot on social media. These findings support the assertion that a lot of people were interested in discussing the Anti-LGBT campaign. As a result, the results of the study's sentiment analysis demonstrate that Twitter users in Indonesia tend to be more neutral in their responses. In this study, testing data using the Naive Bayes method in RapidMiner tools yielded an accuracy of 86.43%, which is greater than the accuracy of the other algorithms, Decision Tree and Random Forest, which is 82.91%. It can be concluded that the machine learning algorithms are extremely effective in performing sentiment analysis on tweets. To research the effectiveness of these machine learning algorithms, we are implementing the Random Forest algorithm towards our stock market dataset to analyze if it performs better or not.

M. Hakkinen et al. [11] worked on a research paper to conduct sentiment analysis of E-commerce review using lexicon sentiment method. Their aim is to review the methods for the Tokopedia and Shopee online retail sentiment analysis system and analyze their effectiveness. With 400 review data that are taken for performing sentiment analysis, they discover that 230 are positive, 80 are neutral and 90 are negative. They draw the conclusion that Tokopedia has a consistent rate, whereas Shopee comments indicating that when people dislike a product, they really dislike it, but when they like it, they will feel that way consistently. We could utilize the lexicon sentiment method to perform sentiment analysis towards the stock market tweets to observe the diversity of sentiment.

H.S. Hota et al. [4] focuses on performing sentiment analysis using Twitter data involving cases of COVID-19. This study examines sentiment analysis by analyzing the sentiment of six distinct nations—India, the USA, Spain, Italy, France, and the UK—using a Lexicon-based method. Using Twitter data from March 15 to April 15, 2020, techniques based on the Lexicon and Valence Aware Dictionary for Sentiment Reasoning (VADER) lexicon were used to categorize sentiment as Negative, Neutral, or Positive. Based on empirical findings, COVID-19 has a negative impact in practically every country. The UK, out of the six nations taken into account for the SA, has the most negativity, at 23.13%, followed by France, at 22.71%, the United States, at 22.01%, and India, at 18.39%, using a simple lexicon-based technique. India has the lowest level of negativity (31.03%) according to the VADER-based method, while it is 35.92% in France, 35.68% in the UK, and 35.38% in the USA. The majority of the population has been found to be optimistic, which suggests that people are feeling upbeat and embracing opportunities as well as problems during this constrained period of COVID-19.

Haroon Malik et al. [12] suggests a method for estimating how many people watch television programmes that are streamed. This is accomplished by utilizing information from social networks, namely publicly accessible data and sentiment score obtained from sentiment analysis on tweets posted about television programmes using Random Forest classifier. The proposed model was 85% accurate in forecasting how many people would watch the streaming programmes. Additionally, a comparison with other classifiers shows that Random Forest maintains a high F-measure while producing an outstanding mix balance of Precision and Accuracy. However, linear regression requires little time to construct a model in comparison to Random Forest. With this information, we could analyze if Random Forest is suitable for doing sentiment analysis in other domains such as stock market related.

Biswarup Ray et al. [13] performed sentiment analysis and used aspect categorization of hotel reviews to create an ensemble-based hotel recommender system. They gathered a brand-new, comprehensive dataset of hotel reviews that was scraped from TripAdvisor.com. They used a methodical approach, first employing an ensemble of a binary classification known as the Bidirectional Encoder Representations from Transformers (BERT) model, which includes three phases for positive-negative, neutral-negative, and neutral-positive. They then gave a Random Forest classifier these pre-trained word embeddings produced by the BERT models together with other textual features like Word2vec word vectors, TF-IDF of frequent words, subjectivity score, etc. The reviews were then divided into other categories using a method based on fuzzy logic and cosine similarity. Finally, using the aforementioned frameworks, they have developed a recommender system. Their sentiment polarity classification model has a Macro F1-score of 84% and test accuracy of 92.36%. With this information, Random Forest could be achieving a high accuracy when doing sentiment analysis towards our stock market dataset.

3. METHODOLOGY

In this study, the Twitter API will be utilized to scrape data for tweets related to small cap and big cap companies. The Twitter API provides access to a vast amount of real-time data, making it an ideal source for collecting tweets relevant to the targeted companies. By using the Twitter API, we can ensure the collection of recent and up-to-date tweets that reflect the current sentiment towards these companies. The justification for using the Twitter API is its ability to provide a rich dataset of user-generated content, allowing us to capture real-time sentiments expressed by individuals on a popular social media platform.

3.1 Data Preprocessing

Since Twitter is unstructured, it is difficult to preprocess and eliminate the complicated parts of tweets before using them. Data preprocessing eliminates noise and irrelevant content from Twitter data, including tweets about advertisements, news, spam, and unrelated tweets. The actual tweets' contents were neither changed nor deleted during this process. The following natural language processing processes were applied to the tweets:

1. **Remove noise:** Noises such as @ sign, tags, 'RT', URLs, numbers, white space and punctuations are removed.
2. **Remove stop words:** Stop words are common in NLP and include all articles, prepositions, and conjunctions like am, are, an, the, is, etc. They don't contain a lot of discriminatory information. Additionally, it does not contribute much to the sentiment classification process and should be eliminated because it can be found in any text, even tweets.
3. **Lower case:** All sentences are changed into lowercase letters.
4. **Tokenization:** The process of breaking down a sequence of text into smaller units and are typically words. Tokenization is a crucial stage in natural language processing (NLP) tasks because it enables computer analysis, processing, and comprehension of the text.
5. **Lemmatization:** It is a linguistic technique that tries to strip words down to their lemma, or basic or root form. In natural language processing (NLP) activities, the resulting lemma reflects the canonical or dictionary form of a term, enabling better analysis and comprehension of the text. For instance, this process inflicts "ate" to its base, "eat," and eliminates the end of "looked" to produce "look."

3.2 Data Labeling

Next is to label the data which were divided into three primary categories (positive, negative, and neutral). Positive tweets were those that expressed favorable opinions or perceptions about the stock market, while negative tweets were those that expressed unfavorable views or criticism. Neutral was the designation given to tweets that expressed neither positive nor negative emotions [6].

3.3 TF-IDF

The feature of the dataset was extracted using the term frequency-inverse document frequency (TF-IDF). The word frequency score is based on how often a term appears in the document. A statistic called Inverse Document Frequency is used to gauge a word's rarity based on a document [14]. As a result, the TF-IDF score (weight) increases in proportion to the rarity of the phrase and vice versa. As a consequence, a term's TF indicates its frequency, and its IDF indicates its significance across the corpus. Anybody can avoid stop words while simultaneously locating terms with more search traffic and lower competition if a term's content TF-IDF weight is high because the content will always be among the top search results [1].

3.4 Lexicon-based Approach

According to the Lexicon-based method, raw text in a processed structural representation, sentiment is connected to the presence of particular words or phrases in the document [4]. We concentrate on using the TextBlob library as a lexicon-based method for sentiment analysis in the context of the stock market in this research study. The powerful Python package TextBlob offers a straightforward and understandable user interface for a number of natural language processing applications, including sentiment analysis. TextBlob enables effective sentiment categorization of textual data pertaining to the stock market by utilizing its built-in sentiment lexicon, part-of-speech tagging, and other linguistic aspects.

3.5 Machine Learning

In order to be trained and to produce predictions, machine learning models require numerical data [15]. We concentrate on using the Random Forest algorithm as a machine learning method. As part of an ensemble learning technique called Random Forest, various decision trees are combined to provide a reliable and precise classifier. Because of its capacity to manage high-dimensional data, prevent overfitting, and make accurate predictions, it has become more popular across a variety of fields. We aim to build a model capable of predicting sentiment polarity (positive, negative, or neutral) associated with stock market information by training a sentiment classifier using a labeled dataset composed of Twitter tweets.

3.6 ChatGPT

We employed ChatGPT, an AI language model developed by OpenAI, to perform sentiment analysis on a collection of tweets. The goal was to assess whether each tweet reflected a positive, negative, or neutral sentiment. ChatGPT analyzes the sentiment embedded in the text using natural language processing algorithms and contextual comprehension [16]. The dataset consisted of a collection of the same tweets used in section 3 were fed into ChatGPT for sentiment analysis.

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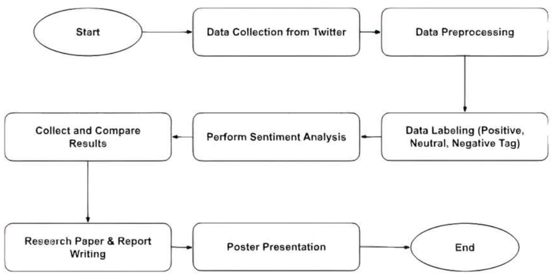

Figure 1: Methodology workflow.

4. EXPERIMENT AND RESULT DISCUSSION

This research is conducted using the Jupyter Notebook environment. In the dataset, we have collected a total of 10,000 tweets using the Twitter API. These tweets are divided into two categories: 5,000 big cap related tweets and 5,000 small cap related tweets with a variety of different companies to provide a diverse range of tweets allowing for a comprehensive analysis of various topics and trends.

For big cap companies there are 3742 neutral tweets, 993 positive tweets and 265 negative tweets. Meanwhile, for small cap companies there are 3300 neutral tweets, 1139 positive tweets and 561 negative tweets.

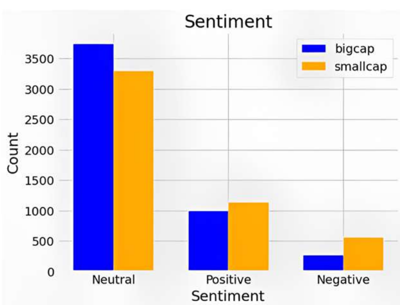

Figure 2: Sentiment of big cap and small cap companies.

4.1 TextBlob

To determine accuracy, the findings were compared to the sentiments that had been manually labeled. When employing TextBlob, the accuracy of correctly labeled was 43.57% for small cap companies and 46.52% for big cap companies. For big cap tweets, the TextBlob algorithm labeled 2389 neutral tweets, 2100 positive tweets and 511 tweets. For small cap tweets, the TextBlob algorithm labeled 2187 neutral tweets, 2188 positive tweets and 625 negative tweets.

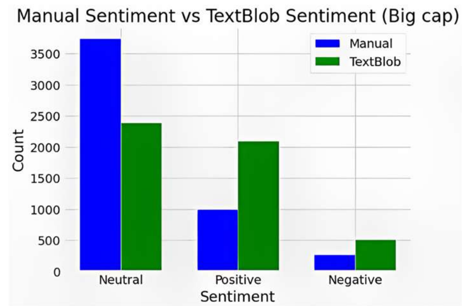

Figure 3: Manual Sentiment vs. TextBlob sentiment for Big Cap.

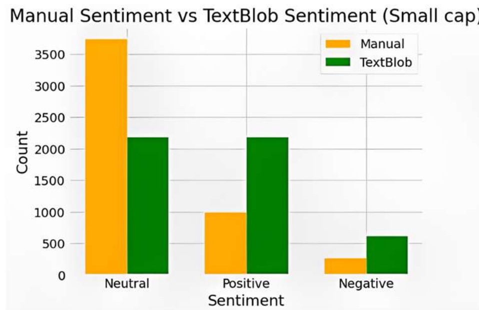

Figure 4: Manual Sentiment vs. TextBlob sentiment for Small Cap.

4.2 Random Forest

Sentiment analysis was performed on the dataset using Random Forest algorithms. The algorithm consists of vectorization using TF-IDF to increase in proportion to the rarity of the phrase and vice versa. When employing this algorithm, Random Forest successfully predicts the sentiment with an accuracy of 83% for big cap tweets and 79.3 % for small cap tweets. The precision and recall of the model which is to accurately identify positive cases and capture all actual positive instances, respectively scores 82% and 83%. The f1-score which offers a balanced measurement of precision and recall scores 81%.

We apply GridSearchCV to perform hyperparameter tuning towards our Random Forest algorithm in order to achieve a higher performance. However, from what we observe, multiple modifications were made but eventually the performance seems to decrease from our initial algorithm. The big cap tweets scores an accuracy of 80%, precision 83%, recall 80% and f1-score 74%. Meanwhile the small cap tweets scores an accuracy of 75.7%, precision 76%, recall 76% and f1-score 66%.

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Table 1. Performance of Random Forest

Cap Sizes	precision	recall	f1-score	accuracy
Big Cap	0.82	0.83	0.81	0.83
Big Cap (Tuned)	0.83	0.80	0.74	0.80
Small Cap	0.79	0.79	0.78	0.793
Small Cap (Tuned)	0.76	0.76	0.66	0.757

4.3 ChatGPT

To obtain the sentiment of ChatGPT, we insert 10 tweets at a time for it to produce the sentiment output. Then, we stored the result in our dataset and analyzed its accuracy. Based on what we observe, the ChatGPT correctly predicts the sentiment with an accuracy of 77.44% for big cap tweets and 72.43% for small cap tweets.

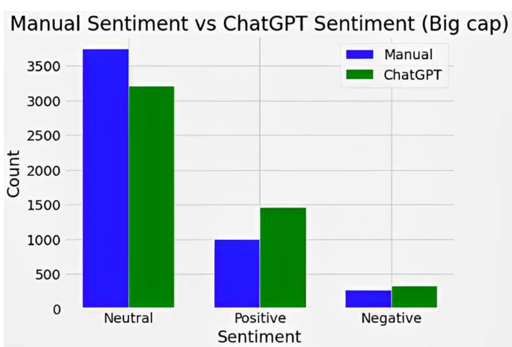

Figure 5: Manual Sentiment vs. ChatGPT sentiment for Big Cap.

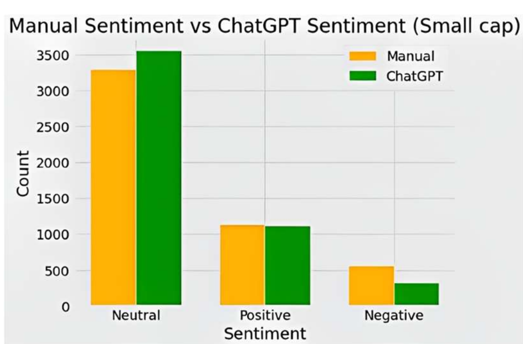

Figure 6: Manual Sentiment vs. ChatGPT sentiment for Small Cap.

4.4 Performance Comparison

Based on the results table, we can observe the Random Forest scores the highest accuracy overall with 83.6% on big cap and 78.8% on small cap. These scores are considered acceptable results. ChatGPT sentiment has an accuracy of 77.44% on big cap and 72.43% on small cap. Meanwhile the lowest performing method is the TextBlob which has an accuracy of 46.52% on big cap and 43.57% on small cap.

Table 2. Performance comparison of 3 methods

Methods	Cap Size	Accuracy (%)
TextBlob	Big cap	46.52
	Small cap	43.57
Random Forest	Big cap	83.6
	Small cap	78.8
ChatGPT	Big cap	77.44
	Small cap	72.43

4.5 Discussion

The evaluation of these 3 methods for sentiment analysis provided valuable insights by their performances. We are able to attain our objective to identify which method is the best for sentiment analysis on stock market tweets. From the results, TextBlob achieved the lowest accuracy among the methods. However, the stock market is a complex and ever-changing environment. There are many slang terms and phrases that are used in the stock market that are not included in the TextBlob dictionary. This means that TextBlob may not be able to accurately understand the sentiment of tweets that contain these terms. For example, TextBlob seems to not understand the term 'bagholder' which indicates the trader holding a stock that has lost a lot of value. It classifies it as a neutral sentiment even though it is a negative tweet.

On the other hand, Random Forest achieves the highest accuracy on both cap sizes category. Because Random Forest can understand the context of tweets, it can reliably determine the sentiment of tweets. This is due to the fact that each Random Forest decision tree is trained using a distinct subset of tweets. This enables the trees to learn the various ways in which tweet sentiment may be communicated. Additionally, Random Forest is able to handle slang terms and phrases that are not included in a lexicon-based dictionary. This is because each decision tree in the Random Forest is able to learn the meaning of words and phrases based on the context in which they are used.

The last method that is used is ChatGPT sentiment analysis. ChatGPT is a large language model that has been trained on a massive dataset of text and code. This makes it very good at generating text that is similar to human-written text. However, ChatGPT is not as good at understanding the sentiment of text as Random Forest. It is not specifically trained on stock market tweets so it may not be as familiar with the slang terms and phrases that are used in the tweets. In addition, ChatGPT is a language model that is not specifically designed to identify the sentiment of text. Even though it is more focused on generating text that is similar to human-written text, the performance for performing sentiment analysis is considered acceptable.

5. CONCLUSION

The evaluation of the three sentiment analysis methods (TextBlob, Random Forest, and ChatGPT) for stock market related tweets showed that Random Forest achieved the highest accuracy overall. This is due to the fact that Random Forest is able to understand the context of tweets and handle slang terms and phrases. ChatGPT also performed well, but it was not as accurate as Random Forest. ChatGPT is still a good option to obtain the sentiment output but it is a tedious and hard task to get the sentiment since we need to insert the tweets one by one to get the result. Sometimes the website slows down and we need to wait some time for it to run smoothly again. TextBlob has the lowest accuracy, but it is still a simple and easy-to-use method that can be used for a quick analysis of tweets.

For future works, researchers can combine the lexicon method and the machine learning method to achieve a higher sentiment accuracy from the stock market related tweets. On the other hand, ChatGPT is still under development to improve and it could perform better in later days. Researchers may use ChatGPT plus to optimize the usefulness of this tool to get better results.

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