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Sentiment Analysis on Twitter through Machine Learning: A Comprehensive Approach with User-Centric Visualisations

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Abstract:- Sentiment analysis is a crucial field that deals with the intricate task of identifying and systematically categorizing the various perspectives and opinions expressed within the original text. In today's digital age, social media platforms serve as a prolific source of data, inundated with a relentless stream of status updates, tweets, and content imbued with sentiments. Analysing the sentiments conveyed by users in this vast reservoir of data holds a pivotal role in comprehending the collective sentiments of the user community, dissecting dialogues, and aggregating viewpoints. This, in turn, can be instrumental in shaping strategies for commerce, conducting insightful political research, and gauging the pulse of communal activities. Examining sentiments on Twitter presents an increased difficulty because of the frequency of spelling errors, casual language, icons, and emojis. This research focuses on Twitter sentiment analysis, with a specific emphasis on a particular user account. The approach involves a combination of Python programming and Machine Learning techniques. By embarking on a comprehensive sentiment analysis journey within a specific domain, the aim is to discern the profound impact of that domain's data on sentiment categorization. Furthermore, this paper introduces a novel feature that enhances the organization of a user's most recent tweets and their presentation through visual aids such as graphs, charts, and word clouds. This visualization approach empowers a more intuitive and insightful exploration of the sentiments and trends embedded within the user's Twitter activity, facilitating a deeper understanding of their thoughts and emotions as expressed through their digital interactions.

Keywords:- *Twitter, Sentiment Analysis, Dataset, User Accounts, Machine Learning Algorithms, Tweets, Data Visualisation*

I. INTRODUCTION

Sentiment analysis, a widely adopted method for extracting insights from text, plays a pivotal role in diverse applications. It leverages innovative text mining techniques to assess the emotional tone of content, categorizing it as positive, negative, or neutral. This analysis is often carried out using programming languages like R and Python, making it a versatile tool for understanding sentiment on platforms like Twitter.

A. Problem Statement

In today's digital age, social media platforms, particularly Twitter, serve as prolific sources of unceasing, unfiltered, and real-time data. Among the myriad applications of this data, sentiment analysis stands out as a pivotal tool for understanding and categorizing the vast spectrum of emotions and opinions expressed within this digital ecosystem. While sentiment analysis on social media data is widely recognized and employed in various domains, there exist several critical research gaps that warrant attention. This research aims to address these gaps and contribute to the field of sentiment analysis by focusing on the following key challenges:

- *Handling Noisy and Informal Text*

Social media platforms, especially Twitter, are rife with colloquial language, abbreviations, misspellings, and emoticons, which pose challenges for accurate sentiment analysis. This paper aims to develop effective techniques for preprocessing and cleaning such noisy data to improve the accuracy of sentiment categorization.

- *User-Specific Sentiment Analysis*

Existing sentiment analysis approaches often provide a broad overview of sentiment within a dataset. However, a research gap exists in understanding how the sentiment of individual Twitter users evolves over time. This paper seeks to address this gap by exploring user-specific sentiment analysis, providing insights into the changing emotional landscape of individual users.

- *Data Visualization for Enhanced Interpretation*

While sentiment analysis results are valuable, conveying these insights effectively to users is a challenge. This paper aims to fill a research gap by introducing and evaluating various data visualization techniques, such as word clouds, bar graphs, and pie charts, to enhance the interpretability and usability of sentiment analysis results.

- *User Engagement and Sentiment Relationship*

Understanding the connection between sentiment and user engagement on Twitter is vital for businesses and individuals aiming to leverage the platform effectively. This paper seeks to address the research gap related to the relationship between sentiment and user engagement metrics like likes, retweets, and replies.

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- *Real-Time Sentiment Analysis*

In the era of instant communication, real-time sentiment analysis is essential for businesses and organizations. The paper aims to contribute to the research gap surrounding the implementation and application of real-time sentiment analysis on social media platforms, with a focus on Twitter.

The approach utilized for sentiment analysis involves an examination of the libraries and tools employed, the data retrieval process involving the Twitter API, and the data cleaning processes indispensable for the interpretation of sentiment. This combines subjectivity and polarity metrics to assess the opinions and sentiments within the collection of tweets, categorizing them as positive, negative, or neutral. The integration of visual representations, such as word clouds, bar graphs, and pie charts, augments the comprehensibility of the sentiment analysis outcomes, thereby presenting an all-encompassing depiction of the emotional dynamics underpinning the user's Twitter activity.

The outcomes of the sentiment analysis provide a valuable insight into the user's emotional involvement with Twitter. By discerning the emotional pulse of the user's tweets, this analysis not only reveals the prevalent sentiment within the Twitter activity but also explicates the user's tendencies, preferences, and interactions with their digital audience. This understanding is instrumental in a myriad of applications, from enhancing marketing strategies and public safety measures to predicting political outcomes and fostering a more empathetic and informed societal approach.

II. LITERATURE REVIEW

The security of the Kirchhoff-law-Johnson-noise's protected vital exchange system is assessed, emphasizing the identification of vulnerabilities and strengthening the overall security infrastructure. [1] New clustering algorithms are introduced, specifically K-means and DENCLUE, to analyse sentiments expressed in tweets. These methods aim to group similar sentiments for more in-depth analysis. [2] Researchers scrutinize various pre-processing methods and test them on two different datasets to evaluate their effectiveness in improving sentiment analysis results. [3] An advanced Recurrent Neural Network - Long Short-Term Memory is deployed on the extensive Twitter database to categorize individuals' viewpoints as positive or negative sentiments. The study evaluates the accuracy of these results by comparing them with various machine learning algorithms, specifically examining sentiment analysis in the distinct context of Twitter data. [4] Sentiment analysis is employed to evaluate the model's efficiency in social media, using standard performance metrics such as accuracy, recall, precision, and F1 score to assess its effectiveness. [5] Twitter sentiment analysis is utilized as an example to expedite rapid decision-making in the FTSE stock market by leveraging predictive abilities based on sentiment analysis results. [6] DICET (Data Integration and Correlation Engine for Twitter) is employed to acquire and align data features to extract essential information, enhancing the quality of data used in sentiment analysis. [7] A groundbreaking method for Qualitative Spatial Reasoning transforms semantic data analysis for private documents, highlighting the power of using spatial relationships to understand confidential content. [8] A cutting-edge sentiment analysis framework is crafted through the implementation of advanced ML techniques, notably Entropy maximization and Simple Bayes. This system excels in categorizing and scrutinizing sentiments conveyed in textual data. [9] Twitter data related to the COVID-19 pandemic is analysed to reveal emotional and attitudinal dimensions in public conversations during this global health crisis. [10] A framework was applied to recognize and categorize sentiments expressed by Twitter users related to a specific product or commodity, valuable for understanding customer opinions and preferences. [11] Using various machine learning methods, sentiment dispersion on Twitter is investigated, utilizing SentiDiff—a novel method considering emotional reversals—to categorize sentiments, alongside developing a predictive model. [12] The paper investigates how individuals express feelings and moods amid the COVID-19 pandemic, specifically on platforms like Twitter, to understand the dynamics of their thoughts and feelings. [13] A novel method is introduced to enhance aspect reduction in sentiment analysis, utilizing advanced mathematical analysis and n-grams to create a tailored Twitter sentiment lexicon. The approach leads to a substantial boost in sentiment classification accuracy. [14] Twitter sentiment analysis of information concerning ordinal reversion is explained, likely focusing on understanding how sentiment changes over time. [15] This research explores sentiment analysis automation for online opinions using machine learning approaches (SVM, Naive Bayes, Decision Tree, KNN) and deep neural network (RNN-LSTM). RNN-LSTM achieves the highest accuracy (88-93%) on Twitter datasets (IMDB, Amazon, Airline) compared to other algorithms. [16] The research paper introduces a unified framework for Twitter sentiment analysis, addressing classification challenges. The proposed hybrid scheme incorporates slang, emoticon, SentiWordNet, and domain-specific classifiers, improving accuracy by considering various linguistic elements in tweets. [17] The study employs the VADER Sentiment Analyzer for multi-classification sentiment analysis of Twitter data related to the 2016 US election, yielding accurate results. Limitations include small data volume and lack of training, with plans to enhance the system in future research. [18] The research evaluates 28 Twitter sentiment analysis systems, highlighting challenges such as brevity, sentiment class imbalance, and stream-based generation and poor performance (average accuracy 61%). Domain-specific models and higher recall improve event detection. [19] The study presents an advanced Twitter sentiment analysis model, combining word embeddings, n-grams, and sentiment features in a deep convolutional neural network. Outperforming baseline models, it demonstrates the efficacy of pre-trained word vectors. [20] This research proposes an ensemble classifier for Twitter Sentiment Analysis, combining base classifiers (Naive Bayes, Random Forest, SVMs, Logistic Regression) to enhance accuracy. The results demonstrate superior performance over standalone and majority voting classifiers, applicable for product monitoring and consumer decision-making. [21]

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III. METHODOLOGY

A. *Libraries*

The program relies on the utilization of several essential libraries to facilitate various tasks. These libraries are as follows:

➢ *Tweepy*

It is a Python library for accessing the Twitter API. It provides functions and classes to interact with Twitter, such as fetching tweets, posting tweets, and managing user accounts.

➢ *Text Blob*

It is a library for natural language processing and sentiment analysis. It simplifies text processing tasks and offers sentiment analysis capabilities.

➢ *Word Cloud*

It is used to create word clouds, which are visual representations of word frequencies. In this project, it's used to generate a word cloud from the tweet data.

➢ *Pandas*

It is a powerful data manipulation library in Python. It is used for creating and manipulating data in tabular form. It's used to create a data frame to store and work with tweet data in the project.

➢ *NumPy*

It is a library for numerical computations in Python. While it's not explicitly used in this code, it's often used in data analysis and manipulation tasks.

➢ *Re*

It is Python's built-in library for regular expressions. It's used to perform text cleaning and preprocessing by removing specific patterns (e.g., mentions, hashtags, hyperlinks) from the tweet text.

➢ *Matplotlib*

It is a library for data visualization. It provides functions for creating various types of plots and charts. In the project, it's used to visualize sentiment analysis results.

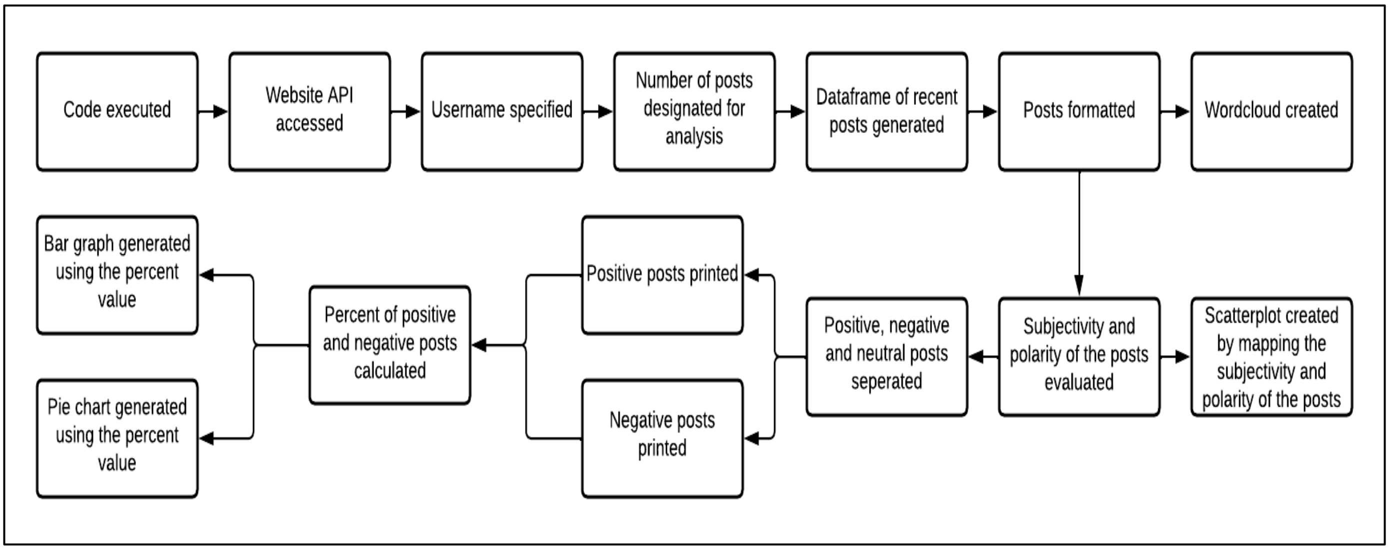

Fig 1: Flowchart Illustrating the Sequential Process for Conducting Sentiment Analysis on Twitter

B. *Twitter API Interaction*

➢ *Twitter API Credentials*

To initiate interaction with the Twitter API, an API object is instantiated, equipped with the necessary credentials obtained from the Twitter developers' forum. These credentials encompass the ‘consumerKey’ and ‘consumerSecret’. These application-level credentials are crucial for the program to authenticate and gain access to the Twitter API programmatically. Once the authentication object is created and populated with these credentials, it sets the user-specific credentials, ‘accessToken’ and ‘accessTokenSecret’, effectively forming an API object ('API') through which the program communicates with Twitter's API. This API object serves as the gateway for retrieving tweets from the specified Twitter account.

➢ *Creating the Authentication Object and Setting the Access Token*

The ‘tweepy.OAuthHandler’ class is used to create an OAuth authentication handler called ‘authenticate’. This handler is configured with the ‘consumerKey’ and ‘consumerSecret’. It's a necessary step to access the Twitter API securely. After creating the authentication object, the access token and access token secret are set using the ‘set_access_token’ method. This step associates the script with the specific Twitter account authorized through these credentials.

➢ *Creating the API Object*

The ‘tweepy.API’ class is employed to create an API object named ‘api’. This object allows interaction with the Twitter API using the authentication previously set up with ‘authenticate’. The ‘wait_on_rate_limit=True’ parameter

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means that the script will wait if it reaches Twitter's rate limits when making API requests.

➢ *Data Acquisition - Extracting Tweets*

The user is requested to enter the Twitter username of the account they want to analyse, along with the desired count of the most recent tweets to extract from the dataset. In this case, the specified Twitter handle is that of the US President, Joe Biden, and the number of tweets to be extracted is 50. The ‘api.user_timeline’ method is then employed to obtain the specified number of recent tweets in extended tweet mode and store them in the ‘posts’ variable.

C. Data Preprocessing - Text Formatting and Data Frame Creation

The text from the extracted tweets undergoes formatting to remove extraneous elements such as @mentions, symbols, and hyperlinks. This text-cleaning process is executed by the 'cleanTxt' function, which prepares the text for sentiment analysis by eliminating any irrelevant or distracting information. The ‘apply’ method is then used to apply this function to the ‘Tweets’ column of the data frame. making the text more suitable for analysis. The resultant cleaned tweets are stored in a ‘pandas’ data frame denoted as 'df'. It has a single column labelled ‘Tweets’, where each row contains the content of one tweet. This data frame serves as an organized and structured tabular representation of the tweet data, enhancing its manipulability and analytical potential.

D. Sentiment Analysis

➢ *Subjectivity and Polarity Evaluation*

The ‘TextBlob’ library is utilized to create two essential functions: 'getSubjectivity' and 'getPolarity,' which serve to evaluate the subjectivity and polarity of individual tweets. Subjectivity is a metric that quantifies the extent to which the text expresses opinions or objectives, whereas polarity is indicative of the sentiment contained within the text, classifying it as either positive, negative, or neutral. These two metrics are represented as numerical values to provide a clear understanding of their intensity.

➢ *Classification and Categorization*

Texts having scores of zero are labelled as neutral, those with scores greater than zero are classified as positive, and those with scores below zero are characterized as unfavourable or negative. Subsequently, the tweets that exhibit the most pronounced positive and negative inclinations are further identified and displayed. This categorization process is executed by leveraging the scores assigned to each tweet, enabling the separation of tweets into their respective sentiment categories.

To conduct sentiment analysis and categorize tweets as 'Positive,' 'Negative,' or 'Neutral,' the 'getAnalysis' function is introduced. This categorization is determined by considering the polarity score of each tweet. The outcomes of the sentiment analysis are then incorporated into the data frame, as illustrated in Fig. 2, as a new column labelled 'Analysis,' enabling the easy classification of each tweet.

	Tweets	Subjectivity	Polarity	Analysis
0	If you got your COVID-19 vaccine before June, ...	0.400000	0.100000	Positive
1	Getting our kids fully vaccinated is the best ...	0.456250	0.450000	Positive
2	I'm always inspired by young leaders like Rach...	0.383333	0.283333	Positive
3	From our family to yours, Happy Hanukkah and C...	0.625000	0.525000	Positive
4	Earlier this year, I had a chance to speak wit...	0.450000	0.000000	Neutral
...	...	...	...	...
95	While we were still in the White House, I bega...	0.300000	0.103125	Positive
96	Three Guinness World Records and now the natio...	0.770833	0.254167	Positive
97	Michelle and I sat down with some terrific you...	0.526984	0.080159	Positive
98	If you want to make sure that insiders can't d...	0.694444	0.125000	Positive
99	It's more urgent than ever for Congress to pas...	0.477273	0.318182	Positive

Fig 2: Quantitative Sentiment Analysis of Twitter Content is Facilitated by Examining the Subjectivity and Polarity of the Tweets

Positive and negative tweets are separately displayed using the data frame. The 'df' data frame is arranged in order based on the 'Polarity' column. Tweets with positive sentiment have higher polarity values and tweets with negative sentiment have lower polarity values. This is done using ‘df.sort_values’ with ‘ascending=True’ for positive tweets and ‘ascending=False’ for negative tweets. A ‘for’ loop iterates through the sorted data frame. Inside the loop, it checks the ‘Analysis’ column to determine if a tweet is positive or negative. If it's positive or negative, the tweet number and the tweet text are printed as seen in Fig. 3.

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1) Over the last year, we have seen the grit and determination of the American people in the face of some of the biggest challenges.

2) More than 200 million Americans are vaccinated.
One billion free COVID-19 tests are available for Americans to order.
More than 400 million free masks will soon be distributed to communities nationwide.

We will get through this pandemic together.

3) One year ago, we promised that we would move quickly to deliver results for working families. From getting shots in arms and gett

4) One year ago, we started to write an American story of hope, not fear.
Of unity, not division.
Of light, not darkness.

An American story of decency and dignity.
Of love and of healing.
Of greatness and of goodness.

May this be the story that continues to guide us forward.

5) I've never been more optimistic about America's future.
```

```
1) There's a clear choice in the midterms: there's a party that works for people and is focused on the future—and a party that

2) Tune in tonight as Vice President  and I host a grassroots event to celebrate what we've accomplished this past year and wha


3) : I am profoundly disappointed that the Senate has failed to stand up for our democracy. I am disappointed – but I am not de

4) : Jim Crow 2.0 is about two insidious things: voter suppression and election subversion. It's about making it harder to vote

5) On Martin Luther King, Jr. Day, we must protect the hard-fought gains he helped achieve—and continue his unfinished struggle
```

Fig 3: Tweets Categorised as Positive and Negative amongst the Extracted Tweets

Using the data frame, the positive and negative tweets are printed separately. The data frame 'df' is sorted based on the 'Polarity' column. Tweets with positive sentiment have higher polarity values and tweets with negative sentiment have lower polarity values. This is done using 'df.sort_values' with 'ascending=True' for positive tweets and 'ascending=False' for negative tweets. A 'for' loop iterates through the sorted data frame. Inside the loop, it checks the 'Analysis' column to determine if a tweet is positive or negative. If it's positive or negative, the tweet number and the tweet text are printed as seen in Fig. 3.

➢ *Percentage*

The data frame 'df' is filtered to create a new data frame 'ptweets' and 'ntweets' that only contains positive and negative tweets respectively. The percentage is calculated by dividing the count of positive tweets, represented by 'ptweets.shape[0],' and the count of negative tweets, denoted by 'ntweets.shape[0],' by the total number of tweets in the dataset, 'df.shape[0],' individually. The result is rounded to one decimal place using 'round()'. This yields the percentage of positive and negative sentiments within the tweets, as illustrated in Fig. 4.

```
# Getting the percentage of positive tweets
ptweets = df[df.Analysis == 'Positive']
ptweets = ptweets['Tweets']

round((ptweets.shape[0] / df.shape[0])*100, 1)
```

```
58.0
```

```
# Getting the percentage of negative tweets
ntweets = df[df.Analysis == 'Negative']
ntweets = ntweets['Tweets']

round((ntweets.shape[0] / df.shape[0])*100, 1)
```

```
18.0
```

Fig 4: Percentage of Positive and Negative Tweets amongst the Extracted Tweets

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IV. RESULTS AND DISCUSSION

A word cloud serves as a visualization method employed to represent textual information, with the magnitude of each word mirroring its occurrence or importance. This technique visually portrays the words that appear most often, with word size and colour reflecting their frequency. Consequently, it offers a rapid snapshot of the prevalent terms within the dataset. The size of the word cloud is established by utilizing the 'Word Cloud' library, and its presentation is facilitated through the 'matplotlib' library.

The word cloud in Fig. 5, shows words related to politics and the US presidential election. It reveals the political campaign and vision of the president, the social and environmental issues and policies, the legislative and administrative aspects, and the outreach and mobilization efforts of his political party.

Fig 5: The Word Cloud is Generated to Visually Represent the Most Frequently used Words in the Tweets by the User, Highlighting Significant Terms

A scatter plot is created to visualize the relationship between polarity and subjectivity for all the tweets. It uses 'plt.scatter' to plot each tweet's polarity (x-axis) and subjectivity (y-axis). 'plt.show()' is called to display the scatter plot.

As seen in Fig. 6, the resultant scatter plot indicates that the tweets have a variety of sentiments. Some points are close to the origin, meaning that they are neutral or factual. Some points are far from the origin, meaning that they are strongly positive or negative, or highly opinionated.

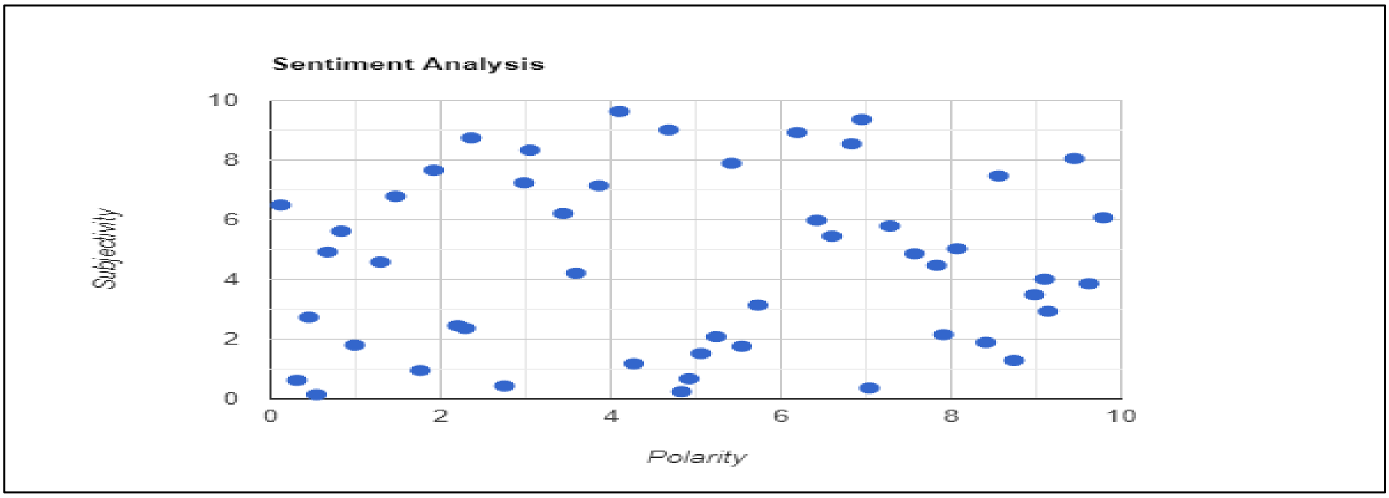

Fig 6: The Graph Depicts the Tweets' Subjectivity and Polarity Relative to Each Other

The 'matplotlib' library is employed to create a graphical representation of tweets based on their subjectivity and polarity. The 'value_counts()' function is used to obtain the counts of each sentiment category in the 'Analysis' column, 'plot(kind='bar')' is used to create the bar chart, and 'plot(kind='pie')' is used to create the pie chart. This visualization is enhanced by using the percentages of positive and negative tweets. The outcomes are showcased in a pie chart and a bar graph, employing unique color-coding to illustrate the distribution of positive, negative and neutral tweets.

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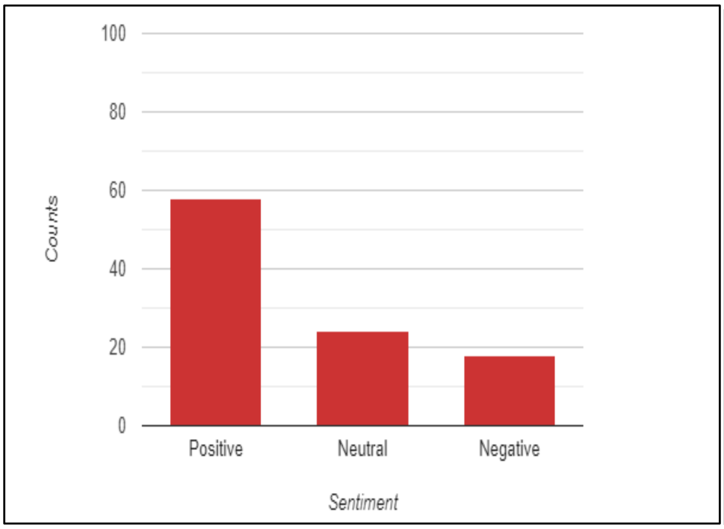
Fig. 7 illustrates the distribution of positive, neutral, and negative sentiments within the textual data through three distinct bars of a bar graph. The positive sentiment has the highest count, approximately 80, followed by the neutral and negative sentiments, both having fewer than 20 counts. Also in Fig. 7, the generated pie chart instead has those three sections represented using distinct colours with the blue (positive) section covering the majority of the chart followed by the orange (neutral) and yellow (negative) sections. Both visualisations indicate that the tweets have a more favourable or optimistic expression than unfavourable or pessimistic ones.



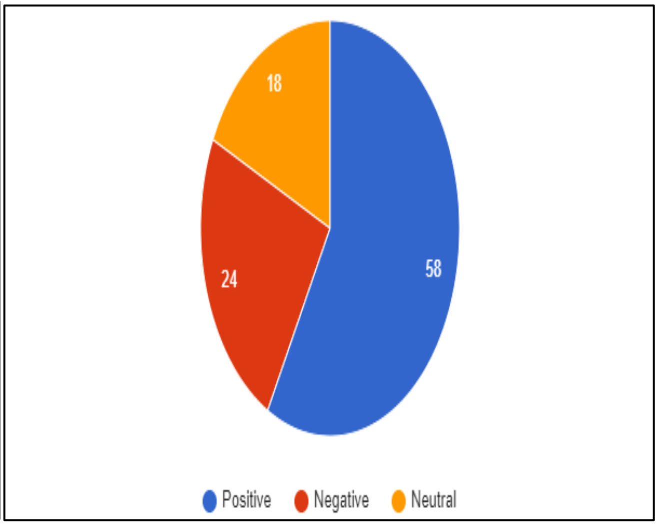


Fig 7: The Bar Graph and Pie Chart Visualization Illustrate the Distribution and Proportion of Counts for Neutral, Positive, and Negative Tweets

V. FUTURE SCOPE

The future of this sentiment analysis project holds significant potential for refinement and expansion. To enhance user engagement, the implementation of an intuitive Graphical User Interface (GUI) would simplify the input procedure. This would enable users to effortlessly enter the Twitter username and designate the desired quantity of latest tweets for analysis. Such user-friendly accessibility would broaden the tool's utility to users with varying levels of technical expertise. While the current system offers compelling visualizations like word clouds, bar graphs, and pie charts, potential avenues include heatmaps, trend graphs, and sentiment over time analysis. These additions would provide more in-depth insights into the temporal dynamics of sentiment within a user's Twitter activity.

Incorporating machine learning and deep learning techniques has the potential to improve the accuracy of sentiment classification. Additionally, exploring context-aware sentiment analysis could enable a more nuanced understanding of language, including sarcasm. Real-time analysis of Twitter data would enable users to monitor evolving sentiment trends and respond proactively to emerging discussions. Furthermore, multilingual support, customizable sentiment categories, predictive analytics, and the integration of sentiment analysis from various social media platforms are all areas that offer substantial potential for future development, making this project a dynamic and evolving tool with far-reaching applications.

VI. CONCLUSION

In this comprehensive research endeavour, a sophisticated python application was developed for sentiment analysis. It is designed to extract valuable insights from the dynamic landscape of Twitter. It not only interacts seamlessly with the Twitter API but also systematically processes and presents data in an intelligible and visually engaging manner.

The program's capabilities include gathering recent and pertinent tweets from a specific user and presenting them in an organized and reader-friendly format. Advanced text mining techniques are harnessed to evaluate the subjectivity and polarity of these tweets, allowing for a nuanced understanding of the emotional content within the text. One of the key features of the program is the creation of a word cloud, a visually intuitive representation of the most frequently used words by the user. This tool provides an immediate grasp of the user's recurring themes and interests. Additionally, the program identifies and highlights the most positive and negative tweets, shedding light on the user's emotional engagement and further enriching the analysis.

The program also calculates the percentage of positive, negative, and neutral tweets within the user's content. This data is then visualized through informative bar graphs and pie charts, offering a clear and compelling depiction of the distribution of sentiment in the analysed tweets. By applying text mining techniques and leveraging the capabilities of Python, the program uncovers and categorizes the emotions expressed in tweets as neutral, positive, or negative.

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The data generated through the sentiment analysis program offers valuable insights into the collective perspectives and sentiments of Twitter users. Such insights are a powerful resource for enhancing decision-making processes, from businesses adapting to customer sentiment to policymakers understanding public concerns and sentiments. In essence, this would facilitate the efficient analysis of social media data and contribute to the broader goals of societal betterment by promoting informed and empathetic responses to the needs and concerns of the public.

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