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TWITTER SENTIMENT ANALYSIS

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ABSTRACT

Advancement in technology has led to a huge volume of data present in the internet. The Internet has become a platform for online learning, exchanging ideas and sharing opinions. Social networking sites like Twitter, Facebook, Google+ are rapidly gaining popularity as they allow people to share and express their views about topics, have discussions with different communities, or post messages across the world. There has been a lot of work in the field of sentiment analysis of twitter data. This survey focuses mainly on sentiment analysis of twitter data which is helpful to analyze the information in the tweets where opinions are highly unstructured, heterogeneous and are either neutral or negative, or positive in some cases. Twitter Sentiment Analysis helps in applications such as a firm which tries to find out the response of the production of the market , political election prediction and prediction of socioeconomic phenomena like stock exchange . Using various machine learning algorithms like Naive Bayes, Logistic Regression and Support Vector Machine, we have used them for conducting the research

Keywords -Log Analysis, Failure Prediction, Text Mining, Machine Learning Algorithms

[1] INTRODUCTION

Nowadays, people communicate their views and beliefs differently thanks to the Internet. Nowadays, it is done primarily through blog postings, internet forums, websites that offer product reviews, social media, etc. Millions of individuals today use social networking sites like Facebook, Twitter, Google Plus, and others to share their thoughts on daily life and express their emotions[1]. Social communities provide an interactive media where users can use forums to inform and influence others. Tweets, status updates, blog posts, comments, reviews, and other types of social media content produce a lot of sentiment-rich data. Additionally, social media gives businesses a chance by offering them a platform to engage with their customers for advertising. The majority of people rely on user-generated content [2].

In the research, different methodologies for sentiment analysis of Twitter data are compared, including machine learning approaches and hybrid approaches that integrate both [2]. The authors assess the effectiveness of different strategies using various datasets and contrast their advantages and disadvantages [3]. The processing, searching, or analysis of the factual material that is present is the core goal of textual information retrieval strategies. While there is an objective component to facts, there are also textual components that represent subjective traits [4]. It is possible to identify patterns by looking at how frequently various parts of speech occur in a class of labeled tweets, either separately or in combination with other parts of speech. These Twitter-based features are more relaxed, in keeping with how people communicate on social media sites, and condensing their feelings [5].

[2] LITERATURE SURVEY

The document gives a summary of the different sentiment analysis tools and sentiment classification methods. Starting with this introduction, the study classifies (i) methods in terms of features/techniques and advantages/limitations, and (ii) tools in terms of the different sentiment analysis techniques [6]. There are numerous applications for sentiment analysis, such as: The essay also touches on commerce, politics, civic engagement, and finance.

The study looks at various strategies and instruments that can be applied in a range of areas, such as business, politics, finance, and public affairs. Sentiment analysis is mostly employed in the business sector to determine consumer attitudes, brand reputation, and the current trends in online marketing and commerce [7]. In the political sphere, voting guidance is a crucial use of sentiment analysis. Additionally, it is utilized to make political positions more clear, which raises the standard of knowledge that voters can access. Sentiment analysis is often used during the public action implementation phase. It significantly aids in the observation of actual happenings in this situation [8].

Another significant use of sentiment analysis is tracking public opinion on upcoming legislative, policy, and regulatory measures. A brand-new, developing area of sentiment analysis is represented by contemporary intelligent transportation systems. Last but not least, sentiment research is employed in the financial sector to spot dangers to the economy as well as trends in the development of stock and commodity prices [9].

[3] SENTIMENT ANALYSIS

Sentiment analysis is a procedure that uses Natural Language Processing (NLP) to automatically mine attitudes, opinions, perspectives, and emotions from text, speech, tweets, and database sources. In a sentiment analysis, opinions in a text are categorized into "positive," "negative," and "neutral" categories. The terms subjectivity analysis, opinion mining, and appraisal extraction are also used to describe it [10].

The words opinion, sentiment, view and belief are used interchangeably but there are differences between them.

- ***Opinion****:* A conclusion open to dispute (because different experts have different opinions)
- ***View:*** subjective opinion
- ***Belief:*** deliberate acceptance and intellectual assent
- ***Sentiment:*** opinion representing one's feelings

The term "sentiment analysis" covers a wide range of activities, including, among others, sentiment extraction, sentiment classification, subjectivity categorization, opinion summarization, and opinion spam detection [25]. It tries to examine people's feelings, attitudes, views, and other characteristics towards many components, including goods, people, ideas, organizations, and services [11].

Mathematically we can represent an opinion as a quintuple (o, f, so, h, t), where

o = object;

f = feature of the object o;

so= orientation or polarity of the opinion on feature f of object o;

h = opinion holder;

t = time when the opinion is expressed.

Object:An entity which can be a, person, event, product,organization, or topic

Feature:An attribute (or a part) of the object with respect to which evaluation is made.

Opinion orientation or polarity:The orientation of an opinion on a feature f represents whether the opinion is positive, negative or neutral .

Opinion holder*:* The holder of an opinion is the person or organization or an entity that expresses the opinion .

In recent years a lot of work has been done in the field of “Sentiment Analysis on Twitter“ by a number of researchers. Here is figure 1 shown ,which represents architecture of Sentiment Analysis :-

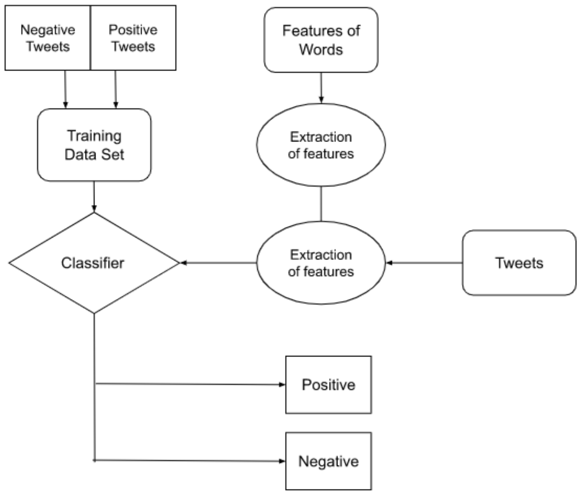

Figure.1 Architecture of Sentiment Analysis

Here are some scientists who have conducted research on sentiment analysis of Twitter [13]:

1. SentiWordNet: SentiWordNet was developed by researchers at Princeton University, including Stefano Baccianella, Andrea Esuli, and Fabrizio Sebastiani. SentiWordNet is a lexical resource that assigns sentiment scores to words, allowing for sentiment analysis of text data.

2. David Garcia: David Garcia is a researcher at the Complexity Science Hub in Vienna who has conducted research on the use of Twitter data for studying political sentiment and opinion dynamics.

3. Bing Liu: Bing Liu is a professor at the University of Illinois at Chicago who has conducted research on sentiment analysis and opinion mining, including applications to social media data such as Twitter.

4. Saif M. Mohammad is a researcher at the National Research Council Canada who has conducted research on sentiment analysis and emotion.

5. Erik Cambria: Erik Cambria is a professor at Nanyang Technological University in Singapore who has conducted research on sentiment analysis and emotion recognition, including applications to social media data such as Twitter.

3.1 Pre-processing of the datasets

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A tweet includes numerous perspectives about the data that are presented by various people in various ways.The Twitter dataset utilized in this study is already divided into two categories, negative and positive polarity, making it simple to perform a sentiment analysis on the data and see how different variables affect sentiment. Polarity in the raw data makes it particularly prone to redundancy and inconsistency [12]. Preprocessing of tweet include following points as shown in figure 2

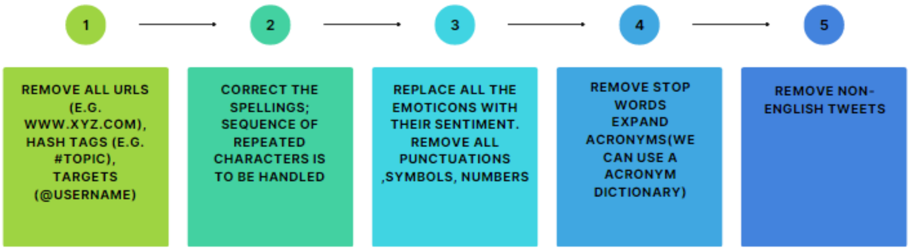

Figure.2 Pre-processing of the datasets

As cited in figure 3 , here is the word cloud representing the positive tweets .

```
[ ]  normal_words= ' '.join([text for text in combine['tidy_tweet'][combine['label']==0]])
     wordcloud= WordCloud(width=800,height=500,random_state=21,max_font_size=110).generate(normal_words)
     plt.figure(figsize=(10,7))
     plt.imshow(wordcloud,interpolation='bilinear')
     plt.axis('off')
     plt.show()
```

Figure.3 Positive tweets Word Cloud

As cited in figure 4 , here is the word cloud representing the negative tweets .

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```
[ ] #racist tweet

    negative_words= ' '.join([text for text in combine['tidy_tweet'][combine['label']==1]])
    wordcloud= WordCloud(width=800,height=500,random_state=21,max_font_size=110).generate(negative_words)
    plt.figure(figsize=(10,7))
    plt.imshow(wordcloud,interpolation='bilinear')
    plt.axis('off')
    plt.show()
```

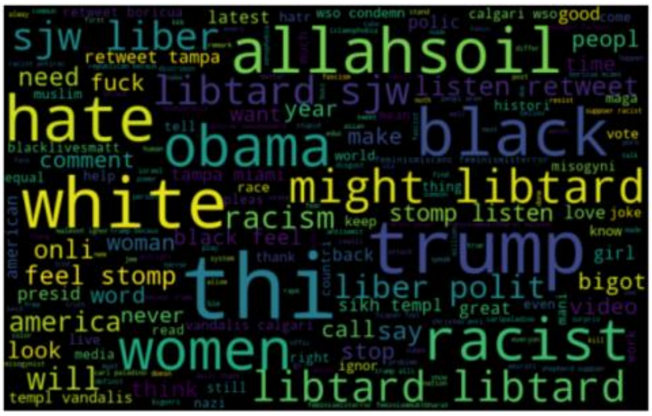

Figure.4 Negative Tweets Word Cloud

As cited in figure 5 , below is the graph for positive tweets of twitter sentiment analysis

```
nonracist_tweets = nltk.FreqDist(ht_regular)
df1 = pd.DataFrame({'Hashtag': list(nonracist_tweets.keys()),'Count':list(nonracist_tweets.values())})

#selecting top 20 most frequent hashtags
df1 = df1.nlargest(columns="Count",n=20)
plt.figure(figsize=(16,5))
ax = sns.barplot(data=df1, x="Hashtag", y="Count")
ax.set(ylabel = "Count")
plt.show()
```

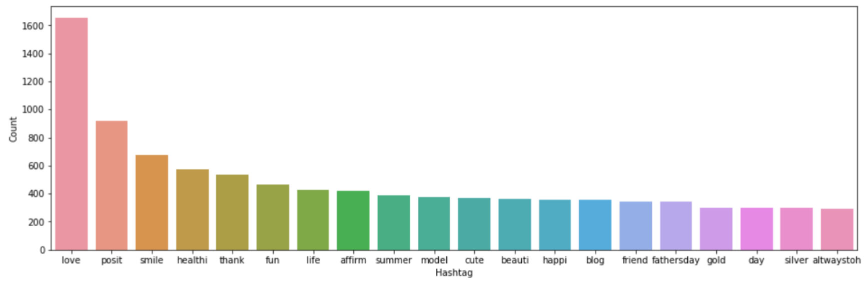

Figure.5 Graph for positive tweets

Figure 6 shows the pictorial representation of graph for negative tweets in twitter sentiment analysis:

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```
racist_tweets = nltk.FreqDist(ht_negative)
df2 = pd.DataFrame({'Hashtag': list(racist_tweets.keys()),'Count': list(racist_tweets.values())}) #count number of occurrence of particular word

#selecting top 20 frequent  hashtags

df2 = df2.nlargest(columns = "Count",n=20)
plt.figure(figsize=(16,5))
ax = sns.barplot(data=df2, x="Hashtag",y="Count")
plt.show()
```

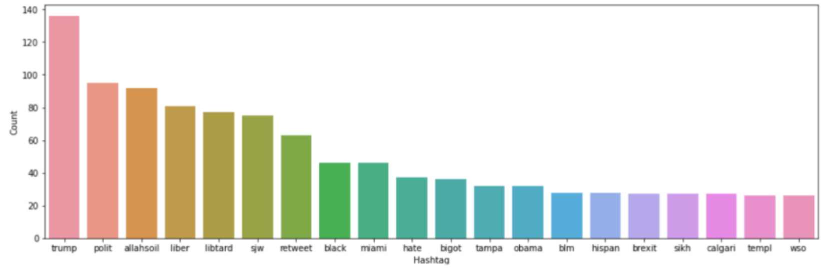

Figure.6 Graph for negative tweets

3.2 Feature Extraction

The preprocessed dataset has a lot of unique characteristics. We take the features from the processed dataset using the feature extraction approach. Later, using models like unigram and bigram [18], this characteristic is utilized to compute the positive and negative paradox in a sentence, which is helpful for determining people's opinions [14]. Twitter sentiment analysis is extracting thoughts and opinions from tweets in order to determine the text's sentiment. Identifying the relevant elements of the tweets that are likely to have an impact on the sentiment expressed is an important stage in this process.

Here are some example features that can be extracted from tweets for sentiment analysis using the techniques [16].

3.2.1 Bag Of Words:

Tweets can be represented as a vector of word frequencies. For example, the tweet "I love pizza" can be represented as [1, 0, 0, 0, 1], where the first element represents the frequency of "I," the second represents "love," and so on.

3.2.2 N-Grams:

A tweet can be represented as a vector of n-gram frequencies. For example, the tweet "I love pizza" can be represented as [1, 1, 0, 0, 0, 0, 0, 0, 0], where the first element represents the frequency of "I love," the second represents "love pizza," and so on.

3.2.3 _Parts Of Speech Tagging:

A tweet can be represented as a vector of part-of-speech tag frequencies. For example, the tweet "I love pizza" can be represented as [1, 1, 0, 0], where the first element represents the frequency of the element represents the frequency of the noun, the second represents the frequency of the verb, and so on.

3.2.4 Emoticons:

A tweet can be represented as a vector of emoticon frequencies. For example, the tweet "I love pizza can be represented as [1, 0], where the first element represents the frequency of positive emoticons and the second represents the frequency of negative emoticons.

3.2.5 Syntax : Syntactic patterns like collocations are used as features to learn subjectivity patterns by many of the researchers.

3.3 Evaluation of Sentiment Classification

The performance of sentiment classification can be evaluated by using four indexes calculated as the following equations: Here in the given diagram TP represents True Positive , TN represents True Negative ,FP represents False Positive and FN represents False Negative respectively as cited in equation 1,equation 2 and equation 3.

Accuracy= $\frac{(TP+TN)}{(TP+TN+FP+FN)}$ ……... Equation 1

Precision = $\frac{TP}{(TP+FP)}$ ………. Equation 2

Recall = $\frac{TP}{(TP+FN)}$ ………Equation 3

F1 =$\frac{(2 * Precision * Recall)}{(Precision + Recall)}$ ………Equation 4

In which TP, FN, FP and TN refer respectively to the number of true positive instances, the number of false negative instances, the number of false positive instances and the number of true negative instances, as defined in the table below.

3.3.1 Confusion Matrix

It is a performance measurement for machine learning classification problems where output can be two or more classes. It is a table with 4 different combinations of predicted and actual values and gives us a matrix as output and describes the complete performance of the model [5].
As represented in table 1 ,a confusion matrix is a table that is used to define the performance of a classification algorithm. A confusion matrix visualizes and summarizes the performance of a classification algorithm.

Table 1: Confusion Matrix

	Predicted Positives	**Predicted Negatives**
Actual Positive	TP	FN
Actual Negative	FP	TN

3.3.2 Training

Supervised learning is an important technique for solving classification problems. Training the classifier makes it easier for future predictions for unknown data.Training is an important part of sentiment analysis, as it involves teaching a machine learning algorithm how to recognize sentiment in text data [6]

3.4 Classification

Here we have considered three classifications as follows :-

3.4.1 Naive Bayes*:*

Naive Bayes is another commonly used algorithm for sentiment analysis. It is a probabilistic algorithm that is based on Bayes' theorem, which states that the probability of a hypothesis (in this case, a sentiment label) given the data (in this case, a piece of text) is proportional to the probability of the data given the hypothesis times the prior probability of the hypothesis [4].

In sentiment analysis, Naive Bayes works by estimating the probability of each sentiment label given the input text based on the frequency of words in the text. The algorithm assumes that the words in the text are independent of each other, which is where the "naive" part of the name comes from.

As cited in Equation 5 , let d be the tweet and c* be a class that is assigned to d, where

C*=arg mac$cPNB(c \mid d)$ ……………Equation 5

P_{NB}(c|d) =$\frac{(P(c))\sum_{i=1}^{m} \quad p(f \mid c)ni(d)}{P(d)}$ …………Equation 6

3.4.2 Logistic Regression:

Logistic regression is a commonly used algorithm for sentiment analysis. It is a type of binary classification algorithm that is well-suited for tasks where the goal is to predict whether a piece of text expresses a positive or negative sentiment [8]. The basic idea behind logistic regression is to model the probability of a given outcome (in this case, whether a piece of text expresses a positive or negative sentiment) as a function of the input features. In sentiment analysis, the input features might include things like the presence or absence of certain words, the frequency of certain words, or the sentiment of certain phrases [6]. Logistic regression makes use of the sigmoid function which outputs a probability between 0 and 1. The sigmoid function with some weight parameter θ and some input x^{(i)}$x(i)$ is defined as follows in Equation 7:-

h(x^(i), θ) = 1/(1 + e^(-θ^T*x^(i))......Equation 7

3.4.3 Support Vector Machine:

Support vector machine analyzes the data, defines the decision boundaries and uses the kernels for computation which are performed in input space [17]. The input data are two sets of vectors of size m each. Then every data which is represented as a vector is classified into a class. Nextly we find a margin between the two classes that is far from any document. The distance defines the margin of the classifier, maximizing the margin reduces indecisive decisions. SVM also supports classification and regression which are useful for statistical learning theory and it also helps recognize the factors precisely that need to be taken into account, to understand it successfully [19].

3.5 Challenges in Sentiment Analysis

Sentiment analysis, like any data analysis task, is not without its challenges. Here are some of the main challenges that researchers and practitioners face when conducting sentiment analysis [20].

Ambiguity: Words and phrases can have multiple meanings, and the sentiment of a particular word or phrase may depend on the context in which it is used. For example, the word "sick" can mean "ill" or "cool" depending on the context, and correctly identifying the sentiment requires understanding the context [24].

Irony and sarcasm: Irony and sarcasm can be difficult for sentiment analysis algorithms to detect, since they often involve saying the opposite of what is meant. For example, the phrase "nice weather we're having" might be used sarcastically to indicate that the weather is actually terrible [25].

Negation: Negation is another challenge for sentiment analysis, since words that indicate negation (such as "not" or "never") can completely reverse the sentiment of a sentence. For example, the sentence "I'm not happy with this product" has a negative sentiment, despite the presence of the word "happy."

Domain-specific language: Sentiment analysis algorithms may perform poorly when applied to text data from domains they have not been trained on. This is because sentiment can be expressed differently in different domains, and the algorithms may not be able to pick up on these nuances [26].

Data availability and quality: Finally, one of the biggest challenges in sentiment analysis is data availability and quality. Sentiment analysis algorithms typically require large amounts of labeled data to train, and the quality of the data can impact the accuracy of the resulting model [28].

Addressing these challenges requires ongoing research and development in the field of sentiment analysis, as well as a deep understanding of natural language processing and machine learning techniques .

3.6 Approaches for Sentiment Analysis

One of the main techniques for sentiment analysis for the twitter data is:

Machine Learning Approaches:-
Machine learning based approach uses classification techniques to classify text into classes. There are mainly two types of machine learning techniques :-

Unsupervised learning: It does not consist of a category and they do not provide the correct targets at all and therefore rely on clustering.

Supervised learning: It is based on a labeled dataset and thus the labels are provided to the model during the process. These labeled dataset are trained to get meaningful outputs when encountered during decision making [10].

The success of both these learning methods mainly depends on the selection and extraction of the specific set of features used to detect sentiment. The machine learning approach applicable to sentiment analysis mainly belongs to supervised classification [23]. In a machine learning techniques, two sets of data are needed:

1. Training Set - A training data set is a data set of examples used during the learning process and is used to fit the parameters.

2. Test Set - A test set in machine learning is a secondary (or tertiary) data set that is used to test a machine learning program after it has been trained on an initial training data set.

[4] RESULTS AND DISCUSSION

Now we will analyze different results we have received based on the calculations.

4.1 Feature Table:

Twitter sentiment analysis, a feature table is a matrix that contains a set of features (words, phrases, or other relevant characteristics) and their corresponding frequency or occurrence in a collection of tweets. The purpose of the feature table is to represent the features that are most relevant to the classification task and to help identify patterns and relationships between the features and the sentiment labels[21].

In table 2 ,below is the feature table of twitter sentiment analysis:

Table 2: Feature Table

FEATURES	WORDS	TOTAL WORD COUNT
POSITIVE	GOOD, THANKS, LIFE, LOVE, SMILE, BEAUTIFUL, FRIEND FAMILY, AFFIRM, WEEKEND, GIRL, BLESS, EXCITE, HOPE, NICE, PROUD	214973
NEGATIVE	AFRIAD, DAMAGE, WORRIED, DISAPPOINTMENT, CONDEMN, FORBIDDEN, REMOVED, TIRED, PATHETIC	214970

4.2 Result Table

We have represented in table 3 that in Twitter sentiment analysis, a result table is a table that summarizes the performance of a classification model on a set of labeled tweets. The purpose of the result table is to provide an easy-to-read summary of the model's performance metrics, such as accuracy, precision, recall, F1 score, and confusion matrix.

Table 3: Result Table

METHOD	PRECISION	RECALL	ACCURACY
NAIVE BAYES	0.417	0.384	0.667
LOGISTIC REGRESSION	0.222	0.575	0.995
SUPPORT VECTOR MACHINE	0.196	0.623	0.956

4.3 Comparison Table

In Twitter sentiment analysis, a comparison table is a table that compares the performance of multiple classification models on a set of labeled tweets. The purpose of the comparison table is to help you choose the best-performing model based on various evaluation metrics as represented in table 4 .

Table 4: Comparison Table

METHOD	PERCENTAGE OF DATA SETS		PRECISON	RECALL	ACCURACY
	TRAINED DATA	TEST DATA			
NAÏVE BAYES	80	20	0.417	0.384	0.667
	70	30	0.417	0.391	0.942
	60	40	0.426	0.401	0.944
LOGISTIC REGRESSION	80	20	0.222	0.575	0.995
	70	30	0.208	0.571	0.955
	60	40	0.195	0.593	0.956
SUPPORT VECTOR MACHINE	80	20	0.196	0.623	0.956
	70	30	0.178	0.656	0.957
	60	40	0.158	0.668	0.957

4.4 Ensemble Table

In Twitter sentiment analysis, an ensemble table is a table that summarizes the performance of multiple classification models that have been combined using an ensemble method. The purpose of the ensemble table is to provide an easy-to-read summary of the ensemble model's performance metrics, such as accuracy, precision, recall, F1 score, and confusion matrix shown in table 5.

Table 5: Ensemble Table

DATA	ACCURACY
TEST	0.0104
TRAIN	0.9227
ENSEMBLE	0.7665
• NAÏVE BAYES	0.757
• LOGISTIC REGRESSION	0.765
• SUPPORT VECTOR MACHINE	0.753

[5] APPLICATIONS OF SENTIMENT ANALYSIS

Sentiment analysis, also known as opinion mining, is a process of analyzing the emotions, opinions, and attitudes expressed in text data. Here are some applications of sentiment analysis: [29]

1] Customer feedback analysis: Sentiment analysis can be used to analyze customer feedback data such as reviews, surveys, and social media posts. By analyzing the sentiment expressed in customer feedback, businesses can understand the strengths and weaknesses of their products and services and make improvements accordingly.

2] Brand monitoring: Sentiment analysis can be used to monitor social media and online mentions of a brand. By analyzing the sentiment of these mentions, businesses can identify areas of their brand that are being perceived positively or negatively and take action to improve their brand reputation.

3] Market research: Sentiment analysis can be used to conduct market research by analyzing the sentiment of customer feedback and social media data related to products, services, and brands. By analyzing this data, businesses can gain insights into customer preferences, opinions, and attitudes and use this information to make informed decisions.

4] Customer service: Sentiment analysis can be used to analyze customer support interactions such as emails, chat logs, and call transcripts. By analyzing the sentiment expressed in these interactions, businesses can identify areas where customer support can be improved and take corrective action.

5] Political analysis: Sentiment analysis can be used to analyze political speeches, social media posts, and news articles to understand public opinion on political issues and candidates. This information can be used by political campaigns to shape their messaging and strategies.

6] Healthcare: Sentiment analysis can be used to analyze patient feedback and social media data related to healthcare services. By analyzing the sentiment expressed in this data, healthcare providers can identify areas of their services that need improvement and take corrective action.

[6] CONCLUSION

In conclusion, this research paper on Twitter sentiment analysis has demonstrated the usefulness of sentiment analysis in understanding public sentiment towards a specific topic, brand, or event. The application of machine learning algorithms and natural language processing techniques has allowed for the efficient analysis and classification of large volumes of tweets.The study has highlighted the importance of selecting appropriate data preprocessing and feature extraction techniques, as well as choosing an effective sentiment classification algorithm. The results of the sentiment analysis have provided insights into the sentiment expressed by Twitter users, and have implications for various fields, such as marketing, politics, and public opinion research.However, the study has also identified several limitations and challenges associated with sentiment analysis in Twitter, such as the difficulty of identifying sarcasm and irony in tweets, and the potential bias introduced by the selection of the training data.In this project we have worked on algorithms like Naive Bayes , Support Vector Machine (SVM) , LR i.e Logistic Regression followed by applying ensemble methods . We found the accuracies of the algorithms and compared them .

Overall, this research paper has contributed to the growing body of knowledge on Twitter sentiment analysis and has provided a framework for future studies in this field. As social media continues to play an increasingly important role in public discourse, sentiment analysis in Twitter will continue to be a valuable tool for understanding public sentiment and opinion.

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