TWITTERSENTIMENTANALYSIS

1. ABSTRACT

Social media platforms like Twitter and Facebook have a dark side, despite their popularity. The purpose of this study is to determine the sentiment of tweets on Twitter and analyze the activity of Twitter accounts. Logistic regression is as it demonstrated the highest accuracy in comparison to other algorithms. The Twitter datasets are gathered and split into training and testing data to train the model for sentiment classification of tweets, and then the Twitter account analysis is conducted. Using Logistic Regression, we have received an accuracy score and f1-score of 0.946 and 0.497 respectively.

Keywords - Twitter, Sentiment Analysis, Logistic regression, Text analysis.

2. INTRODUCTION

Sentiment analysis (SA) enables users to determine whether product information is satisfactory before making a purchase. Marketers and firms utilize this analysis data to gain insight into their products or services and tailor them to meet users' needs. Textual information retrieval techniques focus on processing, searching, or analyzing factual data. However, in addition to objective facts, there are subjective elements in textual content, such as opinions, sentiments, appraisals, attitudes, and emotions, which are the focus of sentiment analysis (SA). The abundance of available information on online sources like blogs and social networks presents many opportunities to develop new applications. For instance, recommendations from a recommendation system can be predicted by considering positive or negative opinions about items through SA.

In this paper, we present a comprehensive approach to detect racist and sexist content in tweets using sentiment analysis and logistic regression. The main aim is to categorize tweets into two groups: positive and negative, to assist in identifying and mitigating the dissemination of harmful content on social media platforms. The project is structured into three primary stages: data preprocessing, feature extraction, and classification. The approach employed in this project has yielded satisfactory results in correctly categorizing tweets based on their sentiment, contributing towards reducing the prevalence of harmful content on social media platforms. In future work, it would be worthwhile to investigate the integration of other machine learning algorithms and techniques to enhance the overall performance of the sentiment analysis model.

3. LITERATURE REVIEW

In recent times, identifying hate speech on social media platforms has emerged as a burgeoning research area. Numerous studies have been carried out to develop effective techniques and models to tackle this challenge. The successful detection of racist and sexist tweets can aid in reducing hate speech and holding individuals accountable for their actions. A considerable amount of research has been conducted in this field, producing significant outcomes. In the subsequent section, a few related works on sentiment analysis are briefly discussed.

- Istaiteh et al. conducted a detailed literature review of approaches used to detect racist and sexist hate speech, with a focus on three primary aspects: available datasets, utilized features, and machine learning models. The authors discuss several techniques employed in this field, emphasizing the significance of selecting appropriate features and models for successful hate speech detection. This study serves as a fundamental resource for comprehending the present state of research in identifying racist and sexist content on social media platforms.

- Krupalija et al. conducted experiments with multiple machine learning models, such as k-means clustering, naive Bayes, decision trees, and random forests, using four distinct feature subsets for training and testing. They employed anomaly detection, data transformation, and parameter tuning to enhance the classification accuracy. The results suggest that using the user hate speech index, either alone or in conjunction with other user features, improves the accuracy of hate speech detection. This study highlights the potential of incorporating user-specific features to enhance the performance of hate speech detection models.

- A study worth mentioning is the one by the authors of Citation and Abstract that explores Twitter sentiment analysis using supervised machine learning methods to detect hate speech. They use the Weka software to analyze a dataset of 5,000 tweets and apply two filters - Tweet to Sparse Feature Vector and Tweet to Lexicon Feature Vector - to enhance the accuracy of the model. The study examines different machine learning techniques and concludes that the Random Forest approach performs the best, with a 93% accuracy rate in both cases.

- Sai Ramesh et al. explained how sentiment analysis involves analyzing natural language to determine whether a piece of text contains subjective information and what type of subjective information it conveys, such as positive, negative, or neutral emotions. They conducted data analysis on a large number of tweets as big data and categorized the polarity of words, phrases, or entire documents. They used linear regression to predict tweet polarity and achieved an accuracy of 85.23%. To improve the accuracy of their approach, they applied 10-fold cross-validation.

- In her study, Shikha Tiwari focuses on Twitter Sentiment Analysis as a means to identify the underlying sentiment of individual tweets. She uses Natural Language Processing (NLP) techniques to analyze the language used in tweets. Tiwari found that the application of Random Forest and Decision Tree algorithms improved the precision of the analysis compared to Support Vector Machines (SVM). She concludes that further research and decision-making can benefit from her work.

4. PROBLEM FORMULATION

How is our model going to help in sentiment analysis?
The goal of this project is to develop and implement a Twitter sentiment analysis model using natural language processing (NLP) to accurately classify tweets as positive or negative. The aim is to address the challenges associated with sentiment classification of tweets and provide a solution for identifying the sentiment behind each tweet.

5. DATASET USED

Formally, given a training sample of tweets and labels, the task at hand is to classify tweets as either positive or negative sentiments using an NLP Twitter sentiment analysis model.

The training dataset contains 31,962 tweets with labels where a label of '1' indicates a tweet is racist/sexist and '0' indicates a tweet is not racist/sexist. The goal is to predict the labels for the test dataset. The provided dataset is in CSV format with each line containing a tweet ID, its label, and the tweet.

<u>Training dataset:</u>

To prepare our dataset, we utilized a technique on 31,962 attributes. In order to provide a foundation for further implementation and utilization, initial data collection, known as training data, is essential for neural networks and other artificial intelligence systems. This training data forms the basis of knowledge for the programmed models. We employed Logistic Regression to train these models.

Testing dataset:
The evaluation dataset is an independent dataset used to evaluate the performance of the trained models. It provides an unbiased measure of how well the model performs on new and unseen data. To evaluate our trained models, we used the logistic regression algorithm, which is a popular and effective algorithm for binary classification tasks.

6. METHODOLOGY

The main goal of our study is to develop a model for detecting hate speech in tweets by identifying those that contain racist or sexist sentiments. In this regard, a tweet is considered to contain hate speech if it exhibits racist or sexist undertones. Our objective is to classify tweets into two categories: those that are racist/sexist (labeled as '1') and those that are non-racist/non-sexist (labeled as '0'). Figure 6.1 shows the methodology.

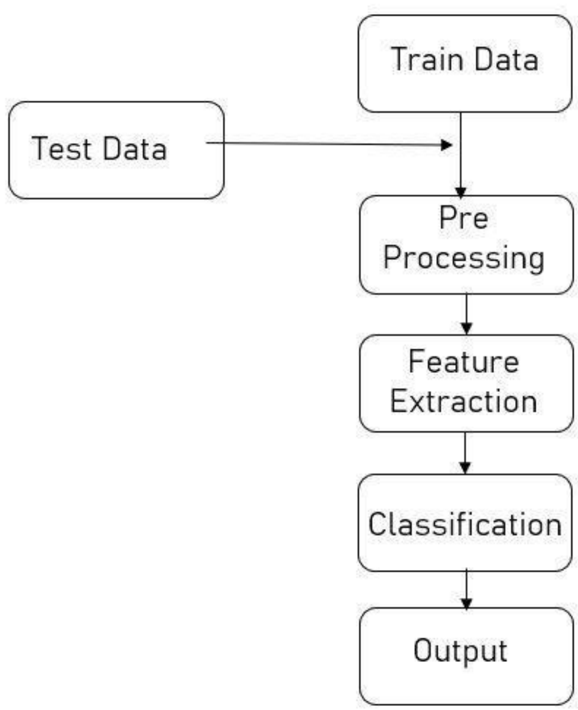

Figure 6.1: Methodology of the work

Pre-Processing- Preprocessing the dataset is crucial for accurate sentiment analysis as it helps to remove noisy and inconsistent data. The aim of preprocessing is to eliminate elements that contribute little to sentiment identification, such as punctuation, special characters, numbers, and terms that have minimal contextual relevance.

Feature extraction- The extraction of features involves selecting and combining variables in order to represent the original data set accurately and completely, while reducing the amount of data to be processed. This process generates informative and non-redundant derived values, which facilitate subsequent learning and generalization steps, and can lead to better human interpretations in certain cases.

Input Split

In [28]:
```
# feature extraction
from sklearn.feature_extraction.text import CountVectorizer
bow_vectorizer = CountVectorizer(max_df=0.90, min_df=2, max_features=1000, stop_words='english')
bow = bow_vectorizer.fit_transform(df['clean_tweet'])
```

Classification- We will use logistic regression to develop these models, as it is a statistical method that estimates the probability of an event occurring by fitting the data to a logit function. Logistic regression is a supervised machine learning algorithm that predicts a binary outcome based on one or more input features, such as true/false or yes/no.

7. RESULT ANALYSIS

For our result analysis, we have tested and trained our model using Logistic Regression. The table below shows the accuracy and F1-score that we have achieved using Logistic Regression. We've also shown the classification output we got from predicted probabilities.

ALGORITHM	ACCURACY SCORE	F1-SCORE
Logistic Regression	0.946	0.497
Using 'probability' for Logistic Regression	0.943	0.554

Model Training

```
In [41]:  from sklearn.linear_model import LogisticRegression
          from sklearn.metrics import f1_score, accuracy_score
```

```
In [38]:  # training
          model = LogisticRegression()
          model.fit(x_train, y_train)

Out[38]:  LogisticRegression()
```

```
In [39]:  # testing
          pred = model.predict(x_test)
          f1_score(y_test, pred)

Out[39]:  0.49763033175355453
```

```
In [42]:  accuracy_score(y_test,pred)

Out[42]:  0.9469403078463271
```

Using Probability to get the scores:

```
In [43]:  # use probability to get output
          pred_prob = model.predict_proba(x_test)
          pred = pred_prob[:, 1] >= 0.3
          pred = pred.astype(np.int)

          f1_score(y_test, pred)

Out[43]:  0.5545722713864307
```

```
In [44]:  accuracy_score(y_test,pred)

Out[44]:  0.9433112251282693
```

The graph below Figure 7.1, plots top 10 positive hashtags on x-axis with its count of the y-axis.

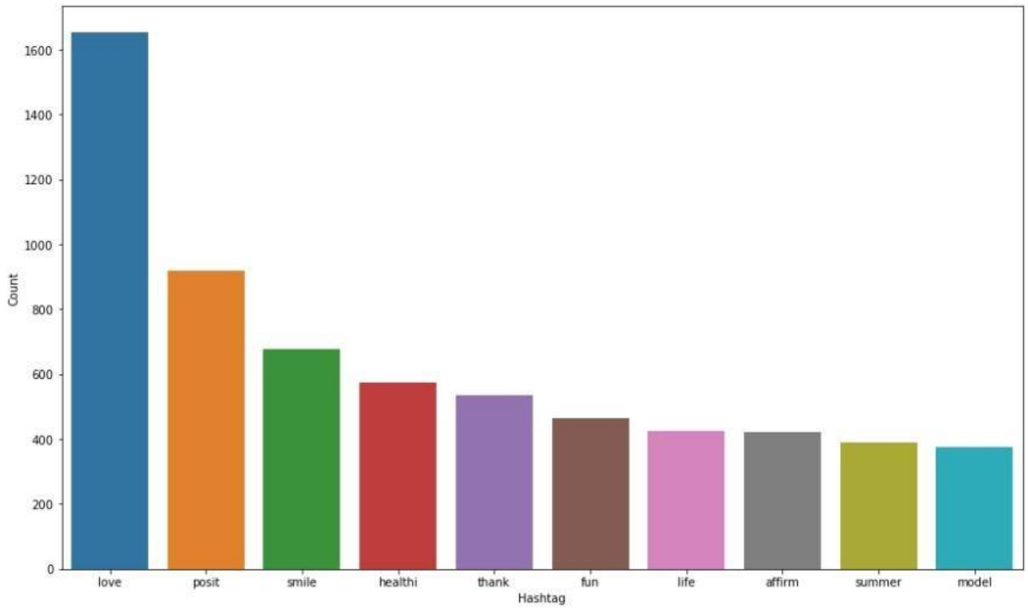

Figure 7.1: Plot for positive hashtags

Where as, Figure 7.2 shows the plot for top 10 negative hashtags with its count.

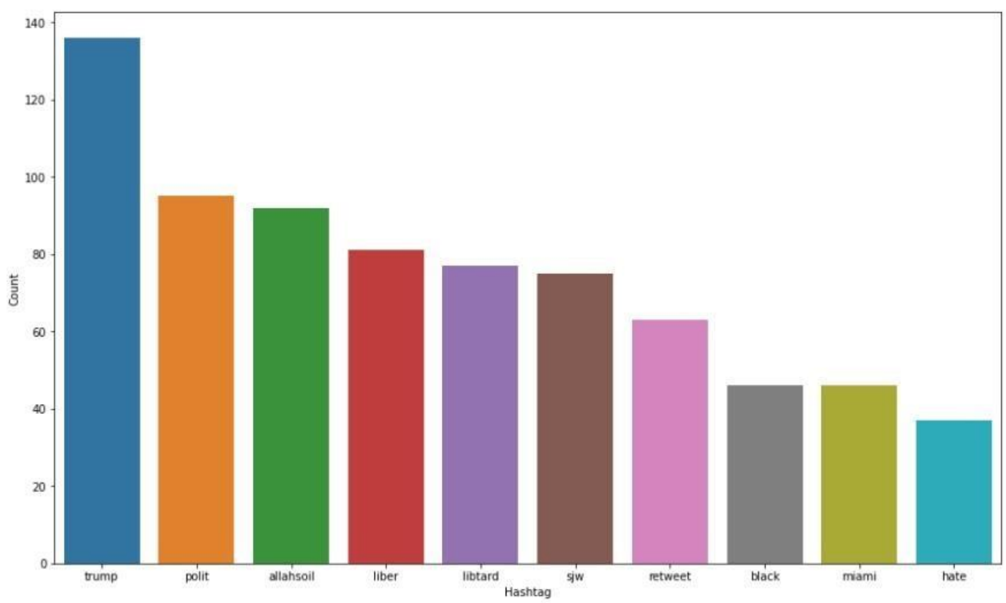

Figure 7.2: Plot for negative hashtags

8. CONCLUSION AND FUTURE WORK

CONCLUSION:

Twitter is a widely used communication platform with approximately 321 million active users worldwide. Many officials use their Twitter accounts to communicate their actions and initiatives to the public. This research project aims to present a novel framework for classifying a Twitter dataset obtained from Kaggle, consisting of approximately 31,962 tweets, using machine learning techniques. The primary objective is to select the most suitable algorithm and metric for the machine learning classifier, as well as to analyze the metrics obtained from various learning algorithms based on the dataset size.

FUTURE WORK:

In the field of sentiment analysis, there exist several opportunities for future research and development. For instance, it is possible to explore various classification algorithms like support vector machines, random forests, or neural networks to determine the most suitable approach for sentiment analysis tasks. Another direction could involve utilizing advanced feature extraction techniques such as word embeddings to capture semantic relationships between words and potentially improve classification accuracy.

To enhance the performance and generalizability of sentiment analysis models, it is crucial to evaluate them on more diverse and extensive datasets that incorporate a broader range of sentiment expressions and domains. Therefore, exploring larger and more varied datasets is a potential future research direction that could help improve sentiment analysis models' functionality and contribute to advancements in natural language processing. We intend to pursue these research paths to enhance sentiment analysis models' capabilities and contribute to the ongoing developments in this field.

9. REFERENCES

[1] Shikha Tiwari, AnshikaVerma, PeeyushGarg, Deepika Bansal. 2020. Social Media Sentiment Analysis On Twitter Datasets.2020 6th International Conference on Advanced Computing & Communication Systems (ICACCS).

[2] S.Siddharth, R. Darsini, Dr. M. Sujithra. 2018. Sentiment Analysis on Twitter Data Using Machine Learning Algorithms in Python. Research Gate.

[3] Tahreem Zahra, Dr Hamid Ghous, Iqra Hussain. 2021. Sentiment Analysis of Twitter dataset using LLE and classification methods.

[4] Antim Antim. 2023. Application of ML in Text Analysis: Sentiment Analysis of Twitter Data Using Logistic Regression. Research Gate.

[5] Shamantha Rai B, Sweekriti M Shetty. 2019. Sentiment Analysis Using Machine Learning Classifiers: Evaluation of Performance. 2019 IEEE 4th International Conference on Computer and Communication Systems.

[6] Amrita Shelar and Ching-yu Huang. 2018.Sentiment Analysis of Twitter Data.2018 International Conference on Computational Science and Computational Intelligence (CSCI).

[7] Rosy Indah Permatasari, M. Ali Fauzi, Putra PanduAdikara. 2018. Twitter Sentiment Analysis of Movie Reviews using Ensemble Features Based Naïve Bayes.

[8] Dr. K. Maheswari. 2018.Improving Accuracy of Sentiment Classification Analysis in twitter Data Set Using KNN.

[9] Vishal A. Kharde, S.S. Sonawane. 2016. Sentiment Analysis of Twitter Data: A Survey of Techniques

[10]Jaspreet Singh, Gurvinder Singh, and Rajinder Singh. 2017.Optimization of sentiment analysis using machine learning classifiers.