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BIG DATA IN ACTION: ANALYZING TWITTER SENTIMENTS THROUGH MACHINE LEARNING AND NATURAL LANGUAGE PROCESSING

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ABSTRACT

Sentiment analysis (SA) is essentially a subfield of data mining and natural language processing that is primarily concerned with the problem of extracting useful knowledge from comments posted by users of the web. However, academic studies of various topics in South Africa have been underway for over than ten years. The method of present study incorporates a machine learning and natural language processing of sentiments on data of twitter. Synthetic Minority Over-sampling Technique (SMOTE) has been employed in the identification of samples that are from the minority class to create synthesized samples. Bag of Words (BoW) is applied here for the extraction of features since textual data require a good representation before further analysis. The evaluation metrics employed are accuracy, precision, recall and F1 score which are applied on several classification models such as MLP, LR and PSO. From the data it emerges that the LR model is the best one in this case with 88% accuracy, 83% precision, 81% recall and 82% F1-score. This paper suggests directions for further research in the subsequent social media analytics by proving the efficiency of machine learning approaches in handling sentiment analysis.

KEYWORDS: Sentiment Analysis, Twitter Data, Social Media, Machine Learning, Natural Language Processing (NLP).

1. INTRODUCTION

Opinion mining has steadily gained interest as a study area since social media is so widely used. Big data features like volume, diversity, and velocity are used in produced social media material, necessitating the use of ML and big data technologies for sentiment/text analysis [1][2]. Sentiment analysis, sometimes referred to opinion mining, which is the method of determining what writers think about particular things.[3][4]v. Sentimental analysis is used in many contexts, such as evaluating whether a product review is positive or negative, determining whether a political party campaign was successful, evaluating movie reviews, and examining tweets or other social media content. Sentimental analysis is often used to understand people's true feelings about a certain product, service, organisation, film, news, event, problem, and its characteristics. Companies and social media monitoring tools rely on machine learning and sentiment analysis to help them understand mentions, brands, and items.

The method of identifying the emotions in a given text is known as sentiment analysis. In other words, a decision has to be made as to whether or not the textual content provides positive or negative comments about the subject or product in the communication. There is another name used for it by different people, and that name is opinion mining[5][6]. It requires students to demonstrate knowledge of artificial intelligence and natural language processing[7], and machine learning [6]. Including, the main concentration of sentiment analysis is on what other

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individuals are saying about a particular subject. Sentiment analysis is highly beneficial for the purpose because it reveals people's opinions regarding a particular product or service and provides important evaluations [8].

Businesses must follow topics in addition to sentiment analysis in order to keep an eye on social media material [5][2]. Numerous academics have previously looked at sentiment analysis and its challenges. We have chosen sentiment analysis of user evaluations using deep learning because of its applicability and impact on the development of several innovative apps. The automated analysis of these texts and the extraction of valuable information has therefore received a lot of attention. Machine-learning algorithms are used to extract this kind of knowledge[9][10]. The study of methods that allow computers to learn from a particular environment is known as machine learning (ML) [6].

Aim and contribution of paper

The aim of the paper Analyzing Twitter Sentiments using ML and NLP is to develop an effective framework for sentiment analysis of tweets to understand public opinion and trends in real time. This project contributes to the ground of data science and social media analytics by providing a comprehensive methodology for analyzing Twitter sentiments. Key contributions include:

- Collect Twitter data to establish a comprehensive framework for sentiment analysis.
- Implements the SMOTE to effectively handle a class imbalance in sentiment distribution, enhancing model robustness.
- Effectively represents textual data in the classification process by using the BOW method for feature extraction.
- To train the logistic regression model for sentiment analysis using data from Twitter.
- Evaluate the efficacy of the sentiment classification model using performance parameters, including accuracy, precision, F-score, and confusion matrices.

Structure of the paper

The research is organised as follows: The review of the literature on the body of research for sentiment analysis is presented in section II. It was used in section III to get the data used in this study. The results of the investigation and discussion of Twitter sentiment are given in Section IV. Last of all, the conclusion on the subject is provided in Section V.

2. LITERATURE REVIEW

The surveys and reviews of publications on machine learning methods for sentiment analysis on Twitter are covered in this part.

In this paper, Wang, Niu and Yu, (2020) focus on integrating sentiment diffusion patterns with text data extracted from tweets to enhance their sentiment analysis results on material available in tweets. As far as we are aware, this is the first study to use sentiment diffusion patterns to enhance sentiment analysis inside the Twitter setting. Numerous experiments on authentic datasets reveal that the proposed approach enhances PR-AUC outcomes by 5.09%- 8.38% in diverse distinctive Twitter sentiment classifications when correlated with the most cutting-edge textual information sentiment analysis algorithms[11].

In this paper, Tusar and Islam, (2021) have discovered a successful method for sentiment analysis on a large, imbalanced, multi-class dataset that combines five machine learning classification algorithms—SVM, Random Forest, Logistic Regression, Multinomial Naive Bayes, and BFS—with two natural language processing features, BFS and TF-IDF. The maximum accuracy of 77% was attained in this work using the Bag-of-Words approach in conjunction with Support Vector Machine and Logistic Regression[12].

This study, Siswanto et al., (2021) Examine sentiment suggestions regarding culinary data from large Javan cities' food or cuisine. A tweet on the culinary skills of the four Indonesian cities served as the data source. In Indonesia, the Sastrawi Library is the algorithm that is used to process text mining data. According to the data, most cities expressed good emotions. The big cities on Java's island offer delicious food and should be recommended for enjoyment, as shown by the four cities' combined emotion rating of 54%[13].

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The two primary methods of sentiment analysis used in this study, Wazery, Mohammed and Houssein, (2018) are some of the algorithms employed, including the DNN, an RNN using LSTM and SVM, naive Bayes, DT, and K-nearest neighbour. Additionally, we used two methods using three Twitter datasets: IMDB, Amazon, and Airline. The experiment results and the comparison of other algorithms are also shown, demonstrating that the recurrent neural network employing LSTM achieves the maximum accuracy of 88, 87, and 93 percent[14].

This paper introduces a novel hybrid method for sentiment classification that combines neural networks with text mining. Abd El-Jawad, Hodhod and Omar, (2018) analyses the effectiveness of other ML and DL techniques. Over a million tweets gathered across five domains make up the dataset utilised in this study. This is shown by the fact that the hybrid learning method of the system maximizes system accuracy at 83.7% as compared to supervised learning methods[15].

In this work, Ismail et al., (2018) opinionated trends about exploiting Sudanese Arabic dialect tweets to analyze the quality of telecommunications services in Sudan is done as follows. For this study, classification models were developed using four trained classifiers with 4712 tweets in total. More precisely, the following classifiers were employed: K-Nearest Neighbour, SVM, Multinomial Logistic Regression, Naïve Bayes, etc., in the purpose of evaluating the accomplishment of these classifiers. When all these algorithms were applied to the Twitter dataset, it was evident that the model with the highest F1-score was the SVM, which scored 72.0, and the highest accuracy was scored by the KNN with parameter (k=2); the accuracy scored was 92.0[16].

The summary of the above background study based on methods, data, findings, and limitation of their work are presented in Table 1

Table 1: Summary of background study for Analyzing Twitter Sentiments Through Machine Learning

Author	Methods	Dataset	Results	Limitation/future work
Wang, Niu, and Yu (2020)	Sentiment diffusion analysis; SentiDiff iterative algorithm	Twitter data	improvements in PR-AUC from 5.09 to 8.38%	Further exploration of sentiment reversal properties
Tusar and Islam (2021)	NLP methods include TF-IDF and Bag-of-Words; ML algorithms include SVM and Logistic Regression, Multinomial Naive Bayes, Random Forest	Large imbalanced multi-class dataset	77% accuracy with SVM and Logistic Regression	Investigation of additional NLP techniques and algorithms
Siswanto et al. (2021)	Sentiment analysis on culinary data using Sastrawi Library	Tweets from 4 cities in Java	54% cumulative positive sentiment	Expanding analysis to more cities or cuisines
Wazery, Mohammed, and Houssein (2018)	Deep Learning: LSTM; Machine Learning: SVM, Naive Bayes, Decision Tree, K-NN	IMDB, Amazon, Airline datasets	Highest accuracy: 88%, 87%, 93% (LSTM)	Explore other deep learning architectures and datasets
Abd El-Jawad, Hodhod, and Omar (2018)	Hybrid system using text mining and neural networks	1 million tweets across 5 domains	Max accuracy of 83.7%	Development of more efficient hybrid systems
Ismail et al. (2018)	Classifiers: K-NN, Multinomial Logistic Regression, SVM, and Naïve Bayes	4712 tweets in Arabic from Sudan	Accuracy: 92.0 (KNN); maximum F1-score: 72.0 (SVM)	Need for reliable corpus and lexicons for Arabic sentiment analysis

3. METHODOLOGY

For the purpose of analysing sentiments using machine learning and natural language processing. Figure 1 illustrates a flowchart's process for applying a machine learning model to Twitter sentiment analysis. For analysis of sentiment first collected gathering tweets from online sources rather than directly from Twitter. Next, data preprocessing was conducted using Python's NLP toolkit, where tweets were changed to lowercase, URLs,

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punctuation, and stop words were eliminated. and stemming and tokenization was applied. SMOTE was then used to create synthetic samples for minority classes in order to correct class imbalance. The dataset was then divided into training and testing sets (80% for training and 20% for testing), and features were extracted using the Bag of Words (BoW) approach. After classifying data using logistic regression, measures including accuracy, precision, F-score, and confusion matrices were employed to evaluate the model's functionality.

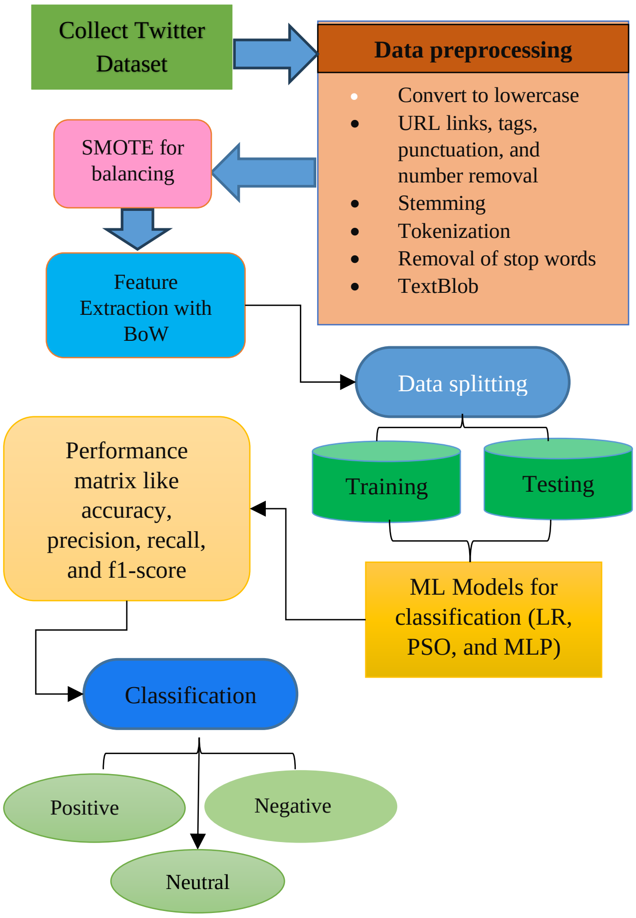

Figure 1: Flowchart for Sentiment analysis

Each steps of following flowchart are briefly explained in below:

A. *Data collection*

Collecting pertinent tweets on a certain topic of interest is known as tweet collecting. The API is used to gather the tweets. We may collect the data for the input with the aid of these APIs. Since it's a time-consuming procedure, data for this study was gathered from a variety of websites rather than tweets from Twitter. The following analysis and visualisation of Twitter data are given below:

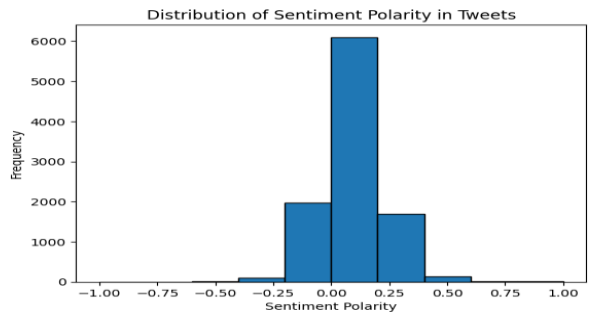

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Figure 2: Histogram for Distribution of sentiment Polarity

Figure 2 shows a right-skewed distribution of tweet sentiment, with a mode around 0.25, indicating more positive than negative tweets. The sentiment range spans from -1 to 1, with a few outliers on the negative side. This provides a quick insight into the sentiment distribution, highlighting overall positivity and some extreme negatives.

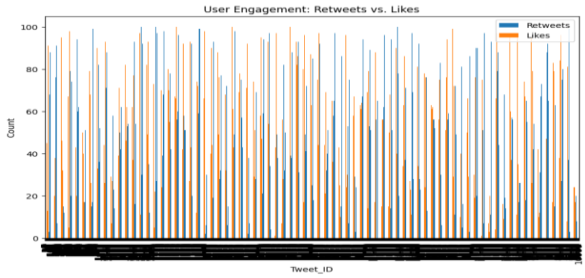

Figure 3: Count plot for retweets and like

Figure 3, comparing retweets and likes across tweets, shows significant variability in engagement, with a positive correlation between the two metrics—tweets with more retweets generally have more likes. While most tweets receive lower engagement, a few outliers with exceptionally high interaction suggest viral content. The distribution is right-skewed, with fewer highly engaged tweets. This analysis can provide insights into the content driving engagement, patterns in user behaviour, and potential influencers within the network.

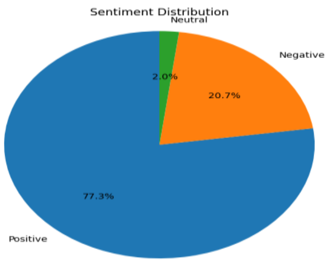

Figure 4: Pie chart for Sentiment distribution

The pie chart in Figure 4 shows that 77.3% of the dataset expresses positive sentiment, while 20.7% is negative, and only 2.0% is neutral. This indicates that the content being analyzed is largely viewed favourably, with a small but notable portion expressing negative sentiment, suggesting some areas of concern. The low neutral percentage may reflect a general lack of ambiguity or strong opinion in the data.

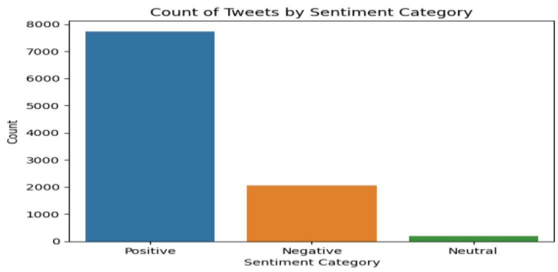

Figure 5: count plot for tweet category

The count plot for the tweet category is displayed in Figure 5 below. The y-axis displays the number of tweets that fall into each of the three emotion categories (positive, negative, and neutral), with values ranging from 0 to 8000.

B. Data preprocessing

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Data preprocessing is necessary for data analysis applications in order to eliminate unnecessary information and speed up the process by which categorisation models are learnt for increased accuracy[17]. In this study, twitter data was preprocessed using Python's NLP toolbox. Tags and After the text has been converted to lowercase, punctuation is eliminated. After that, the text is cleaned using stop word removal and stemming tokenisation procedures, which are finally removed as explained below:

- **Convert to lowercase:** Since machine learning models interpret "go" and "Go" as distinct attributes, changing both words to lowercase will result in "go," which simplifies the feature set. Upper-case and lower-case words are treated differently by models, which has an impact on training and classification results.
- **URL links, tags, punctuation, and number removal:** Since they don't provide models for learning any new meaning [6], they create the feature space. More complicated URL links, tags, punctuation, and numerals don't assist in improving classification performance; hence, eliminating them facilitates feature space reduction.
- **Tokenizing:** The practice of creating a token or term using distinct words from a phrase and its components is known as tokenising.
- **Removal of stop words:** Words that don't offer any useful analysis are frequently employed as stop words. Elimination of stop words such as "the," "is," "a," and "an".

C. TextBlob

The TextBlob sentiment function provides a polarity score ranging from -1 to 1. A tweet with a polarity score of less than zero is considered negative, one with a score of zero is considered neutral, and one with a value greater than zero is considered positive [18].

D. Synthetic Minority Oversampling Technique (SMOTE)

SMOTE balances the number of samples in each class in a dataset to solve the problem of imbalanced datasets [19][20]. By producing fictitious minority class samples, balance is achieved by having almost as many minority class samples as the class that is in the majority. The sentiment ratio is not equal after using Text Blob, which might cause models to overfit on the dataset that is unbalanced. SMOTE prevents this issue of over-fitting by balancing the sample by fabricating information for the minority group. Figure 6 displays the sentiment ratio.
Prior to and following SMOTE application.

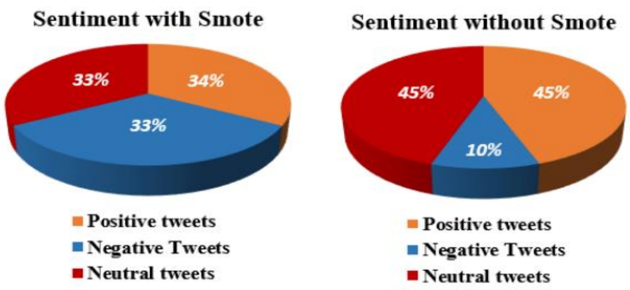

Figure 6: sentiment with and without SMOTE

After using SMOTE to remedy class imbalance, the pie charts demonstrate a notable shift in the sentiment distribution. At first, just 10% of tweets were negative, whereas 45% of tweets were neutral or good. After applying SMOTE, the sentiment distribution shifts from being imbalanced (positive and neutral at 45%, negative at 10%) to a more balanced state, with each sentiment category (positive, negative, neutral) making up about one-third of the dataset. This helps improve model performance by addressing the original class imbalance.

E. Feature extraction with BoW

BoW employs the most popular feature extraction techniques for tweet feature extraction. BoW is a straightforward method for extracting characteristics from condensed text or data that is frequently applied in information retrieval and natural language processing [38]. The BoW is mostly used to train learning models using the frequencies of all unmatched words and expand the vocabulary of all of them.

F. Data splitting

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Splitting dividing the dataset into test and train sets is very important for training the model and calculating the accuracy of the model. Training data contains 80% of data the remaining part of data 20% used for testing.

G. Classification with Logistic Regression

It is an algorithm for supervised machine learning that uses a certain class as its output. It calculates the likelihood using its logistic function. The probability is calculated as (1):

$$P(X) = \frac{1}{1+e^{-(a+bX)}} \qquad (1)$$

- The input variable is X.
- The natural logarithm's base is e
- The weights of the logistic regression model are denoted by a and b.

The value of $P(X)$ approaches 1 as X gets closer to ∞, and it approaches 0 as X gets closer to -∞. This may be shown in Equation 2. The logistic function's output falls between 0 and 1, containing both.

$$y = \begin{cases} 1, if\ P(X) \geq 0.5 \\ 0, otherwise \end{cases} \qquad (2)$$

In order to forecast class from $P(X)$, we must apply a threshold, which, according to Equation 2, is 0.5 and should be the lowest value required to be classified in class 1.

H. Performance metrics

Quite the opposite for the models derived with classification algorithms: a confusion matrix was applied. The four measures of performance that were used were accuracy, precision, F-score and measures of scale. The evaluation of the ability to accurately point out to the True Positive class, where 'Y' = Yes is referred to as the sensitivity while the ability to correctly estimate for the True Negative class where Y=No is referred to as the specificity. When the model classifies the data into negative class while in actual It's a constructive class. False Negative (FN) is the term for this, while False Positive (FP) is the term for when the data is classified as positive when it is actually negative. Following performance measures are as follows:

1) Accuracy

Crucial variables for accuracy Finding the classifiers' accuracy is one of the crucial variables to take into account while providing data estimations. Any prediction model's accuracy may be expressed as (3):

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+Fp+TN+FN}} \qquad (3)$$

2) Precision

It is the percentage of documents correctly assigned to the positive prediction class relative to all documents in that class. It is written as (4)

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \qquad (4)$$

3) Recall

It is determined by the formula of the ratio of the total sample that is relevant to the total sample of accurate positive results. It is expressed mathematically as (5):

$$Recall = \frac{\text{TP}}{TP+FN} \qquad (5)$$

4) F1-score

The weighted average of recall and accuracy is known as the F1-score. Both false positives and false negatives are taken into consideration by the F-Score. It is expressed mathematically as (6)

$$F1 - Score = \frac{2(Precision*Recall)}{\text{Precision+Recall}} \qquad (6)$$

These matrices are utilized to determine the machine models.

4. RESULT ANALYSIS AND DISCUSSION

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The experiment results of ML models for sentiment analysis are presented in this section. The Twitter dataset is used to test the following models, which are assessed using a performance matrix that includes f1-score, recall, precision, and accuracy. The LR model to attain the best performance is shown in Table 2 below.

Table 2: ML model Performance on Twitter dataset

Performance matrix	Logistic Regression
Accuracy	88
Precision	83
Recall	81
F1-score	82

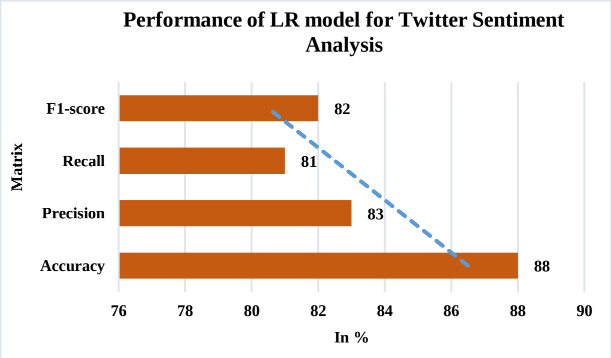

Figure 7: LR model Performance on Twitter data

The subsequent performance of the LR model is displayed in Table 2 and Figure 7. In this figure, LR achieved strong performance metrics in this sentiment analysis task, with an accuracy of 88%, indicating the model correctly classified a high proportion of the data. Logistic Regression achieved 83% precision, meaning 83% of predicted positives were correct, and 81% recall, indicating its ability to capture actual positives. The model is useful for sentiment categorisation because of its 82% F1 score, which demonstrates a decent balance between accuracy and recall.

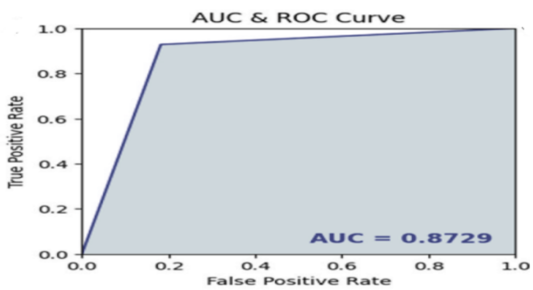

Figure 8: AUC & ROC curve for LR model

Figure 8's ROC curve for the LR model shows how the TP Rate and FP Rate are traded off. With an AUC of 0.8729, the model demonstrates strong classification performance, effectively distinguishing between positive and negative instances. While the model performs well, further analysis is recommended to ensure its suitability for the specific application.

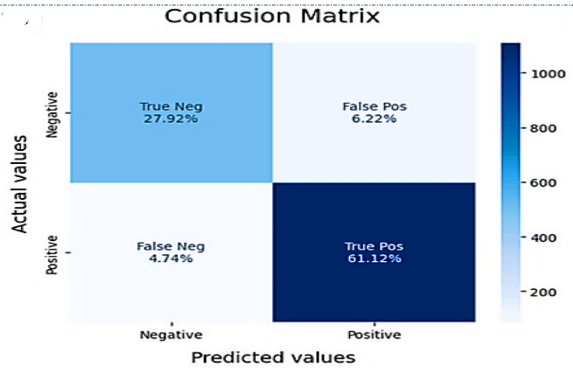

Figure 9: Confusion matrix for LR model

Figure 9's LR model's confusion matrix illustrates how well it categorises cases. It correctly classified 27.92% of TN and 61.12% of TP, while incorrectly classifying 4.74% as FN and 6.22% as FP. This detailed breakdown helps evaluate the model beyond overall accuracy by considering measures like as F1-score, recall, and accuracy for a more thorough evaluation of performance.

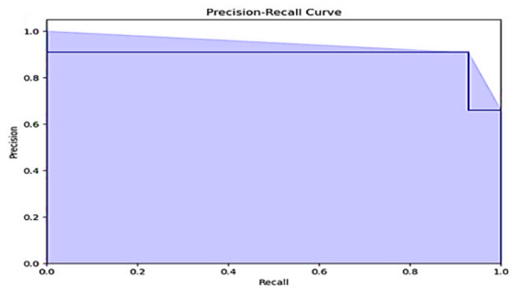

Figure 10: Precision-Recall curve for LR model

The Precision-Recall curve for the Logistic Regression model shows how precision varies with recall, providing insights into the model's balance between the two metrics shows in figure 10. An ideal curve would be in the top-right corner, representing high precision and recall. A steep curve indicates a good balance, while a flat one suggests difficulties maintaining precision as recall increases. Understanding the trade-offs between recall and accuracy depending on categorisation criteria is made easier by the curve, and its comparison with other models, alongside domain knowledge, aids in evaluating the model's overall suitability for the task.

Table 3: ML models comparison on the Twitter dataset for Sentiment analysis

Matrix	**PSO**[21]	**MLP**[22]	**LR**
Accuracy	80.54	75	**88**
Precision	73.98	73	**83**
Recall	50.17	74	**81**
F1-score	59.79	73	**82**

The following Table 3 shows the comparison between model performance on twitter data. For sentiment analysis, the LR model outperforms the other models, showing a great balance between accuracy and recall, with 88% accuracy, 83% recall, and 82% F1-score, precision, 81%. The PSO framework, while achieving a decent accuracy of 80.54%, struggles with lower recall, 50.17% and F1-score, 59.79%, suggesting it has difficulty identifying positive instances. The MLP model shows a more balanced performance with precision, recall, and F1-score all around 73-74%, but lags behind LR in overall effectiveness. Overall, LR demonstrates superior performance in this sentiment analysis task.

5. CONCLUSION AND FUTURE WORK

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In the internet age, sentiment analysis is essential because of the wide variety of social media and corporate applications. Sentiment analysis draws inspiration from the fact that it offers consumers' perspectives on the product, hence enhancing its quality. It also facilitates making judgements about manufacturing and purchases. This study successfully demonstrates the effectiveness of sentiment analysis of Twitter data using machine learning and natural language processing techniques. According to the results, the model that performed the best was Logistic Regression (LR), with an accuracy of 88% and precision, recall, and F1-score values of 83%, 81%, and 82%, respectively. These findings highlight the potential of LR for analysing sentiment in social media contexts. The application of preprocessing methods, including Class imbalance was successfully corrected by the SMOTE, which strengthened the sentiment analysis's resilience. However, this research has limitations that must be acknowledged. The reliance on tweets collected from various online sources rather than directly from Twitter may affect the dataset's representativeness and generalizability. Future research may entail investigating more complex deep learning models and enlarging the dataset to contain a wider variety of tweets.

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