JCBI
Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 07 Issue 01
2024
Research Article
https://doi.org/10.56979/701/2024

Beyond Classification: Exploring the Potential of NLP and Deep Learning for Real-Time Sentiment Analysis on Twitter

Waleed Ahmed[1], Tehreem Masood[1,2], Hafiz Muhammad Tayyab Khushi[1,2*], Shamim Akhter[3], Muhammad Naushad Ghazanfar[3], and Iftikhar Naseer[1,2]

[1]Faculty of Computer Science & Information Technology, Superior University, Lahore, 54000, Pakistan.
[2]Department of Software Engineering, Superior University, Lahore, 54000, Pakistan.
[3]School of Information Management, Minhaj University, Lahore, 54000, Pakistan.
[*]Corresponding Author: Hafiz Muhammad Tayyab Khushi. Email: muhammad.tayyab@superior.edu.pk

Received: March 01, 2024 **Accepted:** May 22, 2024 **Published:** June 01, 2024

Abstract: Twitter has evolved into a pervasive societal force, serving as a platform for diverse expressions, including official statements, thoughts, and opinions. This study delves into the multifaceted nature of Twitter, conducting a sentiment analysis on an extensive dataset comprising 1.6 million tweets and an additional 24,000 tweets. Leveraging advanced techniques in Natural Language Processing (NLP) and employing machine and deep learning algorithms, our focus lies in refining sentiment analysis methods to identify and mitigate terrorist-related content within social media posts. The study initiates with a comprehensive data preprocessing phase, involving part-of-speech tagging, sentiment score assignment via SentiWordNet, and neutralization of domain-specific words and negations. This meticulous methodology enhances the quality of the data for subsequent analysis. Weighted sentiment scores are then calculated, categorizing tweets into positive, negative, or neutral sentiment categories. To assess the effectiveness of our approach, various machine learning and deep learning algorithms are employed, including ensemble methods such as majority voting and stacking. Results reveal that Bidirectional Recurrent Neural Networks consistently outperform other models, achieving remarkable accuracy rates of 96% and 98% on two distinct datasets. Furthermore, the study explores diverse feature extraction techniques, shedding light on their impact on model performance. The findings of this research contribute to the ongoing discourse on sentiment analysis, particularly in the context of identifying and addressing potential threats within social media.

Keywords: NLP; Sentiment Analysis; Twitter; Anarchy; Social Media; Deep learning; Machine Learning.

1. Introduction

Twitter, a widely adopted microblogging platform, has emerged as a valuable data source across diverse research domains due to its extensive user base and accessible APIs. Researchers leverage Twitter's data for its application in predicting stock market trends, analyzing public opinion on political matters, identifying research frontiers, and conducting sentiment analysis. Notably, the integration of machine learning algorithms in the analysis of Twitter data has garnered considerable attention. Several studies underscore the potential of Twitter data in di-verse applications. For instance, [31] conducted a literature review, affirming Twitter's utility as a predictive sys-tem for events ranging from stock market trends to election outcomes and disease outbreaks. [22] Proposed a method for detecting research frontiers through Twitter data analysis. Sentiment analysis stands out as a prominent application of Twitter data, with studies by [10, 28, 37], offering various approaches to accurately discerning sentiments in tweets. Moreover, Twitter data analysis extends its relevance to disaster management, as demonstrated by [6], who proposed a method for identifying relevant flood-related tweets and extracting location information.

Despite the progress made in Twitter data analysis, challenges persist, including the absence of a standardized dataset for evaluation and the need for more robust algorithms to handle noise and ambiguity.

As we study further, we also get to explore the paper with CNN model [40, 41] that gave us opportunity to make further exploration regarding deep learning as [42] make another progress about it. In response, this study aims to explore the application of machine learning algorithms in sentiment analysis of Twitter data. We will assess the performance of state-of-the-art algorithms on a standardized dataset, compare results, and discuss limitations while proposing avenues for future research. The escalating popularity of sentiment analysis and social media data analysis prompts a need for robust methodologies. [7] Proposed a sentiment analysis model utilizing deep belief neural networks for analyzing COVID-19 Twitter data streams. [27], focused on sentiments towards terrorist attacks, employing a sentiment analysis model. Research has also delved into keyword extraction techniques, as exemplified by [23], who reviewed various methods, and [36], who analyzed their accuracy. Studies such as [17], explored Twitter data to understand public support for organizations like ISIS. The landscape of sentiment analysis extends to crime prediction, as demonstrated by [32] who proposed a hybrid sentiment analysis approach. [24] Surveyed detecting online extremism, while [8] analyzed social media data related to classified crime types. In the context of terrorist detection on Twitter, research by [13, 38, 33] explored sentiment analysis techniques and hybrid approaches, highlighting the effectiveness of combined methods. The multitude of studies reflects the potential of sentiment analysis and social media data analysis, offering valuable insights for future research. How-ever, challenges persist, necessitating ongoing efforts to enhance sentiment analysis accuracy, especially for non-English languages, and to explore broader applications of Twitter data analysis.

2. Literature Review

This study delves into the challenges and prior research associated with the analysis of Twitter data through Natural Language Processing (NLP) techniques. The objective is to offer insights that guide the development and implementation of technology in a transparent, traceable, efficient, and cost-effective manner. The research specifically aims to optimize the process of retrieving Twitter data related to terror-ism. The related work is systematically categorized based on different perspectives, each critically analyzed and presented in tabular form. This structured exploration provides a comprehensive overview of the existing body of knowledge, laying the groundwork for addressing the challenges identified in the study.

2.1. Deep Learning Approach

Applied deep belief neural networks (DBN) [7] to analyze sentiments in COVID-19-related tweets, revealing a predominantly negative sentiment with positive spikes during key events. Their study emphasized DBN's uperiority over traditional models, advocating for its real-time applicability in monitoring public sentiment [7]. In a parallel study, [36] compared Naïve Bayes and NLP for sentiment analysis during the 2018 FIFA World Cup. NLP demonstrated higher accuracy and F1-score, particularly capturing positive sentiments and occasional negative spikes tied to specific events. The authors highlighted the efficacy of NLP in large Twitter datasets for re-al-time sentiment monitoring, while acknowledging the need for further research to enhance accuracy in noisy and ambiguous tweet data [36].

2.2. Sentiment Analysis Approach

Paper [21] employed machine learning for sentiment analysis in tweets related to terrorist attacks, show-casing high accuracy and F1-score. [19] Explored event detection challenges, methodologies, and future directions, offering a comprehensive guide. [32] Proposed a BERT-based hybrid model for crime prediction, emphasizing emotional reactions captured through sentiment analysis. [24] Critically reviewed methods for online extremism detection, highlighting challenges and advocating interdisciplinary collaboration. Malik et al. implemented a real-time sentiment analysis model for Twitter data, forecasting crowd sentiments during public events. [8] Analyzed Turkish social media data to identify crime patterns, showcasing the utility of machine learning algorithms. [22] Introduced a novel approach for detecting research frontiers using Twitter data, demonstrating its efficacy across diverse fields. [6] Utilized NLP techniques to identify flood-related tweets and their locations, contributing to disaster management. [36], detected terrorist tweets using sentiment analysis, with SVM outperforming other classifiers. [12], conducted a literature review on Twitter's predictive capabilities, emphasizing its widespread use across domains and the increasing adoption of machine learning algorithms, particularly deep learning.

2.3. Machine Learning Algorithm Approach

Utilized machine learning [17], to identify users expressing support for ISIS in a large dataset of tweets. Their qualitative analysis revealed themes such as frustration with political and social systems, responding to perceived threats to identity, and rejection of Western values. The study concluded that Twitter is valuable for studying support for extremist groups, providing insights into antecedents of such support. Further research is needed for validation and more sophisticated Twitter data analysis methods. [21], proposed a Twitter Sentiment Analysis System with multi-dimensional analysis, incorporating aspects like polarity, subjectivity, irony, and sarcasm. Using a hybrid approach, they achieved high accuracy (89.1%) in classifying tweets into positive, negative, and neutral sentiments. The system handled unstructured, informal language effectively. [31] Introduced an unsupervised ensemble framework for Twitter sentiment analysis, combining concept-based linguistic methods and machine learning. Using diverse features and various algorithms, their approach outperformed state-of-the-art methods in accuracy, precision, recall, and F1-score. Further evaluation on larger datasets is recommended for validation.

2.4. Time Series Approach

Present a comprehensive review of keyword extraction methods [38], covering statistical, linguistic, and hybrid approaches. They discuss techniques such as TF-IDF, mutual information, and LDA, highlighting the applications in information retrieval, text mining, and natural language processing. The article evaluates the methods based on precision, recall, and F1-score, offering insights for researchers and practitioners. [15] Propose a time series forecasting model using Twitter data to predict terrorist attacks. The recurrent neural network (RNN) architecture, trained on a dataset of past terrorist attacks, demonstrates high accuracy in real-time predictions. The study emphasizes the model's potential as a valuable tool for counterterrorism agencies in predicting and pre-venting attacks. [31], conduct a systematic literature review on the use of Twitter as a predictive system, analyzing 52 relevant papers from 2012 to 2021. They identify sentiment analysis, topic modelling, and network analysis as main techniques, noting the increasing use of deep learning for improved predictive accuracy. The paper concludes that Twitter data is valuable for predicting various phenomena. [13], provide an overview of techniques for detecting terrorist sentiment on Twitter using sentiment analysis. They emphasize the importance of combining multiple sentiment analysis techniques, including machine learning and deep learning methods, to enhance detection accuracy. The paper highlights challenges such as slang and sarcasm and suggests leveraging do-main-specific knowledge for improved results. [4], offer a comprehensive survey of techniques for analyzing and predicting online extremism content on Twitter. Focusing on sentiment analysis, the paper reviews studies using lexicon-based, machine learning-based, and hybrid techniques. The authors stress the need for more accurate and efficient algorithms, standardized datasets, and further research to detect online extremism content in real-time.

3. Methodology

In this work flow of our working as you clearly see we implement data preprocessing techniques and then pos tagging after that we use sentiword to assign word score to our text, but sometime some words have high value that can change the meaning of sentences to avoid this situation we add filter that remove or neutralized negation word and some words that are purely related to terrorist attack like bomb, killing etc. Fig. 1 that will remove the effect of some high value keywords and afterward we calculate the total weight and make polarity according to our formula like if weight will be more than one it will be positive if 0 or in between -1 to 1 it will be neutral otherwise it will be negative and vice versa after that we use machine learning algorithm and deep learning algorithm to find the accuracy.

In the data collection and preprocessing steps, data were sourced from Kaggle, specifically the Sentiment 140 dataset with 1.6 million tweets and another dataset containing hate speech from Twitter with 25,000 tweets. Natural Language Processing (NLP) techniques were applied to enhance the preprocessing. Data cleaning and quality control involved several tasks such as handling missing data, outlier detection and treatment, data validation, consistency checks, accuracy verification, and standardization. Tokenization and text preprocessing were implemented to facilitate further analysis by converting unstructured text into a structured format. Stopword removal and lowering the case were employed as essential text preprocessing techniques to enhance the quality of textual data for natural language processing (NLP) tasks. Special character handling and stemming were also applied to simplify and clean the text. In the context of the thesis work, Part-of-Speech (POS) tagging, in conjunction with SentiWordNet, was leveraged for sentiment analysis.

The process involves selecting a suitable POS tagging library, tagging the text with grammatical categories, and integrating SentiWordNet for sentiment scoring. Negation handling was emphasized as a critical aspect of NLP and sentiment analysis. It involved identifying negation words, determining their scope, reversing polarities, handling ambiguity, and addressing cases of double negation. Negation handling is crucial for accurate sentiment analysis and understanding user intentions. Weight calculation and polarity identification were highlighted as essential processes in sentiment analysis. Word-level weighting and aggregation methods were explained for calculating sentiment scores. Polarity determination involved thresh-old-based classification, polarity lexicons, and machine learning models, rule-based systems, and hybrid approaches. Machine learning algorithms, including SVM, Linear Regression, Naïve Bayes, Decision Tree, and Random Forest, were discussed in the context of classification tasks. These algorithms play a pivotal role in categorizing data points based on input features and are applied in various domains such as image classification, text categorization, and sentiment analysis.

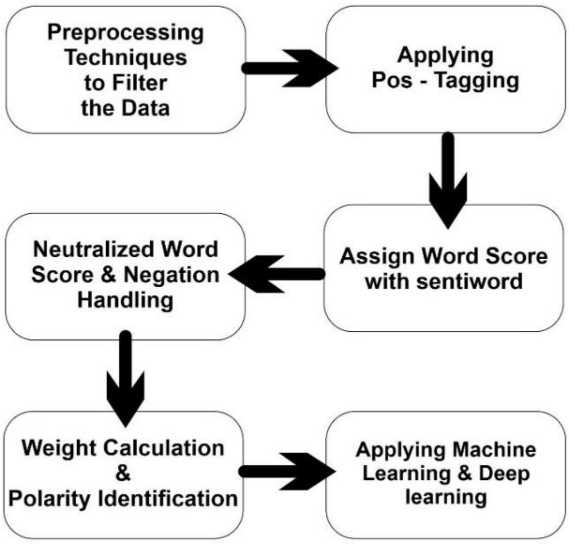

Figure 1. Methodology

The concept of "Domain word neutralization" was introduced, involving the neutralization of domain-specific words to avoid biases in the analysis. It may include changing scores for specific words to zero, ensuring that certain terms do not unduly influence the results, especially in the context of sensitive topics like terrorist-related tweets. The significance of handling negations in sentiment analysis was outlined, emphasizing the identification of negation words, determination of scope, polarity reversal, handling ambiguity, and addressing cases of double negation. Proper negation handling is essential for accurate sentiment analysis and understanding nuanced expressions. Weight calculation and polarity identification processes were detailed, covering word-level weighting, aggregation methods, threshold-based classification, polarity lexicons, and machine learning models, rule-based systems, and hybrid approaches. These processes are fundamental in assessing the overall sentiment expressed in textual data for applications such as product reviews and social media sentiment tracking. Machine learning algorithms, including SVM, Linear Regression, Naïve Bayes, Decision Tree, and Random Forest, were introduced as fundamental tools for classification tasks in machine learning and data analysis. Each algorithm has specific strengths and applications in various domains, providing solutions to classification problems with distinct characteristics.

3.1. Majority Voting

Majority Voting (MV) is an ensemble technique where multiple classifiers, including SVM, Linear Regression, Naive Bayes, Decision Tree, and Random Forest, are independently trained on the same dataset. In MV, each classifier predicts a class, and the final decision is made by selecting the class that receives the majority of votes among the classifiers. This technique is effective when individual classifiers exhibit diverse errors, reducing the impact of noisy predictions and enhancing overall accuracy.

On the other hand, Stacking involves training the same set of classifiers and using a meta-classifier to combine their predictions. The meta-classifier takes the predictions of the base learners as input and learns how to make the final decision. Stacking is beneficial when capturing complex relationships between base classifiers is essential, and it significantly improves predictive performance, especially with variations in the quality of base classifiers.

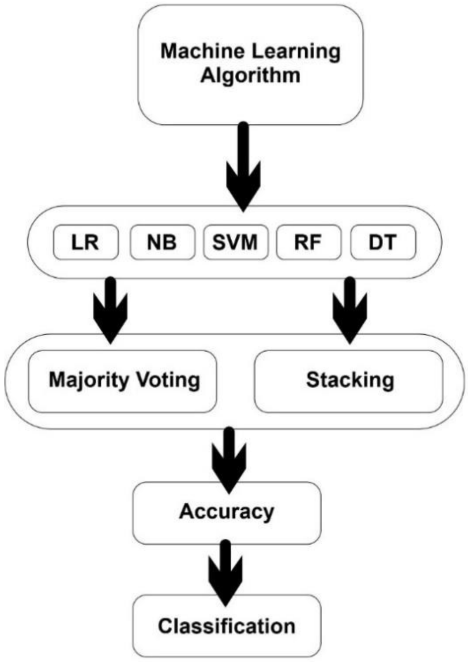

Figure 2. Majority Voting and Stacking

Both MV and stacking contribute to enhancing accuracy and classification performance by leveraging the strengths of multiple classifiers while minimizing their weaknesses as Fig. 2. The choice between MV and stacking depends on specific characteristics of the data and classifiers.

3.2. Machine Learning Classifier

In the methodology, three text vectorization techniques, namely Bag of Words (BoW), N-grams, and TF- IDF (Term Frequency-Inverse Document Frequency), were employed in conjunction with five classification algorithms—SVM, Naive Bayes, Random Forest, Decision Tree, and Linear Regression. Bag of Words represents text as a set of unique words, disregarding order and grammar, and is effective for tasks where word order is not crucial. N-grams, a variation of BoW, consider sequences of N consecutive words as features, capturing some level of word order information. TF-IDF calculates a weight for each word based on its frequency and rarity across a corpus, emphasizing important words while downplaying common ones as Fig. 3. For each classification algorithm, text data is vectorized using one of these techniques, followed by training the respective classifier on the vectorized data and making predictions on new text data. Each algorithm leverages the strengths of these vectorization methods to classify and predict text data efficiently.

3.3. Deep Learning Algorithm

In our study, we employed three distinct deep learning algorithms—Convolutional Neural Network (CNN), Re-current Neural Network (RNN), and Bidirectional RNN—to assess their impact on two datasets, aiming to understand their effectiveness in different contexts. CNNs, renowned for image-related tasks, were adapted for sequential data applications, such as text classification and sentiment analysis. The architecture involved embed-ding layers, convolutional layers for capturing local patterns, pooling layers for dimensionality reduction, and dense layers for classification. RNNs, tailored for sequence data, were applied to tasks where the order of elements matters, leveraging embedding layers, RNN layers for maintaining sequential information, and dense layers for classification. Bidirectional RNNs, an extension of RNNs, excelled in understanding context in both for-ward and backward directions, particularly beneficial for natural language processing.

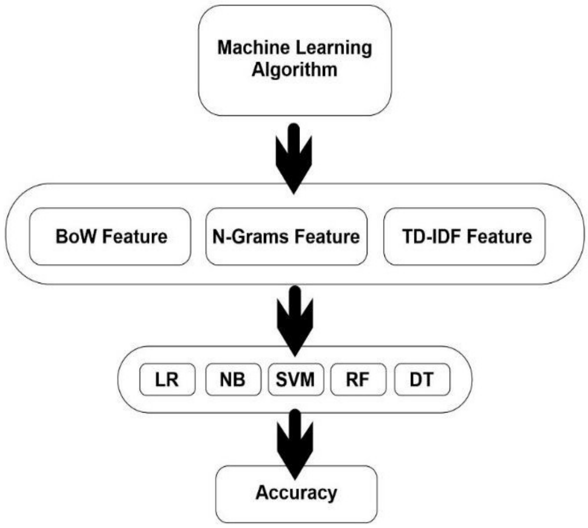

Figure 3. Machine Learning Classifier

The architecture incorporated bidirectional RNN layers in addition to embedding and dense layers. Each algorithm's strengths were harnessed to capture unique aspects of the data, and the impact on accuracy was systematically analyzed. Fig. 4 outlines the hierarchical process undertaken in our experimentation. It's noteworthy that pre-trained embedding like Word2Vec or GloVe were employed to initialize embedding layers, significantly enhancing model performance in text-related tasks

4. Implementation

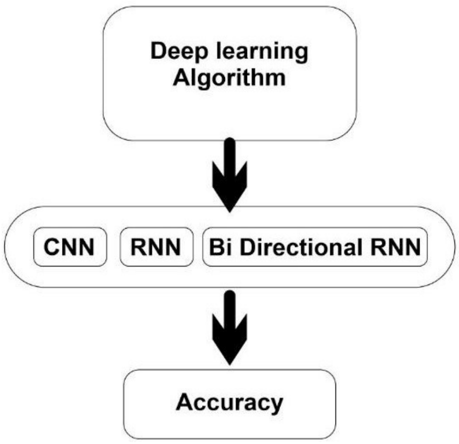

Figure 4. Deep Learning Classifier

The workflow in our study, as depicted in Fig. 1, is a continuous process involving data collection, preprocessing, and the application of various machine and deep learning algorithms for sentiment analysis. In the data collection and preprocessing phase, we obtained our dataset from CSV files, namely "data.csv" and "hate.csv" from Kaggle, and executed essential text preprocessing steps. These steps included lowercasing, removing URLs, HTML tags, punctuation, newlines, and stopwords, as well as tokenization and stemming. The pre-processed data was saved as "preprocessed_data.csv." Subsequently, Part-of- Speech (POS) tagging was implemented using NLTK, and SentiWordNet sentiment scores were assigned to individual words in the pre-processed tweets. This enriched dataset, including POS tags and sentiment scores, was saved as "data_with_pos_tags.csv" and "data_with_sentiment_scores.csv," respectively. The next section focused on neutralization and negation handling. Negation handling was achieved by inverting sentiment scores after encountering negation words, and domain-specific words were neutralized by assigning them a sentiment score of 0.0. The resulting dataset, now containing neutralized sentiment scores, was saved as "data_with_neutralized_scores.csv." The subsequent step involved calculating tweet scores based on sentiment scores and determining overall tweet polarity. This was achieved by summing up sentiment scores and assigning polarity labels (positive, negative, or neutral). The final dataset was saved as "data_with_neutralized_scores_part1.csv." Moving on to machine learning algorithms, we implemented five classifiers—Logistic Regression, Naive Bayes, SVM, Decision Tree, and Random Forest—using three text vectorization techniques: Bag-of-Words (BoW), N-grams, and TF-IDF. The accuracy and F1-score of each classifier were evaluated for each vectorization technique, providing insights into their performance. In the deep learning section, we implemented Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Bidirectional RNN models for sentiment analysis. Each model had specific architectures tailored for processing tweet text. The accuracy of these models was reported after training and evaluation. Lastly, we explored ensemble techniques, including stacking and majority voting, to combine the predictions of multiple classifiers for sentiment analysis. Stacking involved training individual classifiers and creating a meta-classifier, while majority voting determined the final prediction by selecting the most commonly predicted class among classifiers. The accuracy and F1-score of these ensemble methods were calculated. Throughout the implementation, we used visualizations, such as Figure 2, to present a clear overview of the workflow and results, enhancing the interpretability of our methodology. The code for the implementation used libraries like NLTK, Scikit-learn, Keras, and matplotlib. The comprehensive approach, involving both traditional machine learning and deep learning techniques, along with ensemble methods, contributes to a robust sentiment analysis framework with detailed insights into each step's impact on accuracy. Some of the words are here with their related score in Table I that we neutralized.

Table 1. Words and their sentiment score

Word	Score	Word	Score
arrest	-0.125	injured	-2.375
attack	-1.5	murderer	0
attacker	0	shoot	-0.875
attacking	-0.625	shooter	0
blood	0	suicidal	-0.5
bloody	-0.625	suicide	0
killing	0.5	terror	-0.875
killer	-1	terrorism	0
bomb	-0.375	victim	-0.125
bomber	0	weapon	0
broken	-3	wound	-1.375
bombing	-0.125	injured	-2.375
casualty	-1.375	murderer	0
dead	-5.25	shoot	-0.875
deadliest	-2.5	shooter	0
die	-1.25	suicidal	-0.5
death	-1.125	suicide	0
explosion	0	terror	-0.875
explosive	-0.5	terrorism	0
gun	0	victim	-0.125
gunman	0	weapon	0
incident	-0.25	wound	-1.375

5. Result and Discussions

In this part we are going to discuss about the result what we get from our dataset as we mention before that there is two dataset, we are using for our result now our main goal is to get better accuracy from our base paper that have about 94.6 percent accuracy for this purpose we use different classifier and different algorithm to get better results. Now first we will discuss the accuracy and f1 score from the majority voting first than stacking of both data sets then we further move on classifier result and in the end we will discuss about the deep learning result and in the very end we will comparative analysis of each accuracy to get to know which one is better for each dataset.

Table 2. 1.6 MILLION TWEET DATASET SCORE

ALGORITHM OR CLASSIFIER	ACCURACY DATASET 1
Deep learning (RNN)	0.9694
Machine Learning (Stacking)	0.9106
Machine Learning (Majority Voting)	0.9390
Classifier Bag of Words (Logistic Regression)	0.9502
Classifier N-Gram (Random Forest)	0.9480
Classifier TD-IDF(Random Forest)	0.9480

Dataset 1 is common dataset having all types of tweets mix up from the twitter but the second dataset have pure hate speech dataset from the twitter and its way more than shorter than first one and we can clearly see Table 2 the different accuracy and f1score of each section. Now we can present you the distribution of data with polarities.

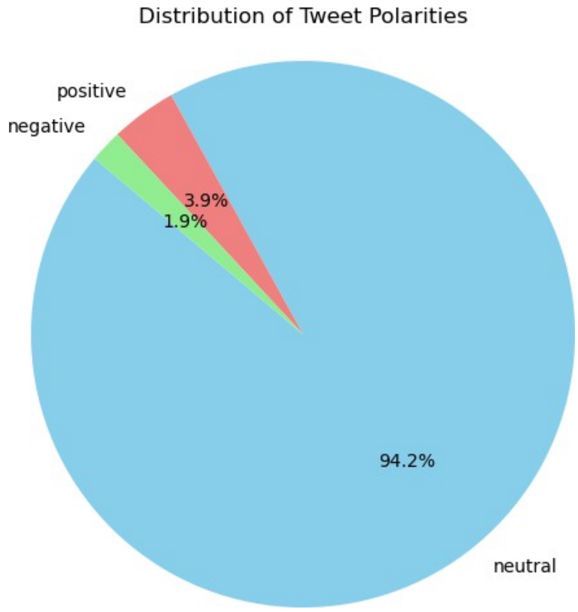

Figure 5. Million tweet dataset

As for this dataset 1 we can clearly see that in Table 2 RNN accuracy is better than all other classifier and machine learning algorithm it is the larger dataset having mix up sentiment half of them are negative comment and half of them was neutral or positive tweets data so concern to this data set RNN is best algorithm that show best accuracy like 96 percent of the accuracy that is better than our base paper accuracy that is 94.6 percent

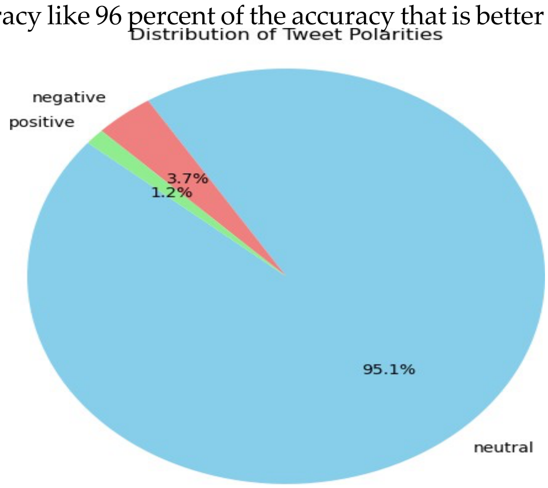

Figure 6. Tweets dataset

As shown in Fig. 5 tell us that neutral and positive data is not related to what our concern but the tweet that fall into negative concern is real data that we can say is tweet we required, and another distribution of polarities in majority voting in second data set is as follow in Figure 6.

Table 3. 24000 TWEET DATASET SCORE

ALGORITHM OR CLASSIFIER	ACCURACY DATASET 2
Deep learning (RNN)	0.9838
Machine Learning (Stacking)	0.9814
Machine Learning (Majority Voting)	0.9836
Classifier Bag of Words (SVM)	0.9878
Classifier N-Gram (Random Forest)	0.9836
Classifier TD-IDF(Random Forest)	0.9834

For the dataset no. 2 having 24k tweets we get best accuracy from Classifier bag of words that is 98.78 percent which are better than other as for concern to this data it is like hate speech each tweet or comment are having hate words and this dataset show overall nearest to 98 percent for all other algorithm and classifier in Table 3.

6. Conclusions

In concluding this research endeavor, our exploration of Natural Language Processing (NLP) and sentiment analysis has resulted in the development of a sophisticated methodology tailored for extracting nuanced sentiments from a corpus of tweets. Commencing with meticulous data preprocessing, including Part-of-Speech tagging, integration of SentiWordNet's lexicon, and intricate techniques for domain-specific word neutralization and negation handling, our methodology is designed for comprehensive sentiment analysis. The foundation of our analytical approach lies in the innovative weight calculation method and polarity assignment. To assess the robustness of our sentiment analysis, we subjected our methodology to a rigorous examination utilizing a diverse set of machine learning algorithms, ranging from traditional classifiers to cutting-edge deep learning models. Incorporating majority voting, stacking techniques, and feature extraction methods, we evaluated the accuracy of our sentiment predictions. Our exploration into deep learning harnessed the capabilities of Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and Bidirectional RNNs, revealing exceptional results that demonstrated the versatility of our approach. The discussion and analysis underscored the efficacy of our methodology across two distinct datasets. In Dataset 1, comprising 1.6 million tweets, RNN emerged as the clear winner with an impressive accuracy rate of 96%, surpassing traditional classifiers and machine learning ensembles. Conversely, Dataset 2, featuring 24k tweets characterized by hate speech, witnessed the supremacy of the Bag of Words approach, achieving an outstanding accuracy of 98.78%.

These findings highlight the adaptability of our methodology to diverse data contexts. In essence, this re-search not only contributes to the field of sentiment analysis but also lays the groundwork for further exploration into real-time sentiment trends and emotion detection within textual content. The innovative approach, characterized by a meticulous blend of traditional and deep learning techniques, opens new avenues for understanding human sentiments in the digital age. Future work in sentiment analysis should explore additional ensemble methods like Adaboost and Gradient Boosting for improved predictive power. Investigating alternative sentiment lexicons, diversifying classifier selection, and extending analysis to multimodal data can enhance accuracy. Challenges include cross-domain analysis, real-time systems, and multilingual capabilities. Standardizing benchmark datasets and metrics will facilitate comparisons, ensuring advancements in accuracy and adaptability for practical applications.

References

1. Y.-C. Yang, C.-H. Hsu, H.-C. Lo and Y.-W. Chien, ―Automatic detection of Twitter users who express chronic stress experiences via supervised machine learning and natural language processing,‖ CIN: Computers, Informatics, Nursing, p. 10–1097, 2022.
2. P. Vyas, G. Vyas and G. Dhiman, ―RUemo—The Classification Framework for Russia-Ukraine War- Related Societal Emotions on Twitter through Machine Learning,‖ Algorithms, vol. 16, p. 69, 2023.
3. A. Van de Weert and Q. A. Eijkman, ―Subjectivity in detection of radicalisation and violent extremism: A youth worker's perspective,‖ Behavioral Sciences of Terrorism and Political Aggression, vol. 11, p. 191–214, 2019.
4. Z. Trabelsi and others, ―A survey of extremism online content analysis and prediction techniques in twitter based on sentiment analysis,‖ Security Journal, vol. 2022, p. 1–28, 2022.
5. Y. Y. Tan and others, ―Sentiment Analysis and Sarcasm Detection using Deep Multi-Task Learning,‖ Wireless Personal Communications, p. 1–25, 2023.
6. M. Suleman and others, ―Floods Relevancy and Identification of Location from Twitter Posts using NLP Techniques, ‖ arXiv preprint arXiv: 2301.00321, 2023.
7. J. Srikanth, A. Damodaram, Y. Teekaraman, R. Kuppusamy and A. R. Thelkar, ―Sentiment Analysis on COVID-19 Twitter Data Streams Using Deep Belief Neural Networks,‖ Computational intelligence and neuroscience, vol. 2022, 2022.
8. S. Savaş and N. Topaloğlu, ―Data analysis through social media according to the classified crime,‖ Turkish Journal of Electrical Engineering & Computer Sciences, vol. 27, p. 407–420, 2019.
9. E. Rosenberg, J. Seo, R. Brinkman and C. Riedl, Sentiment analysis on Twitter data towards climate action, 2023.
10. J. F. Raisa, M. Ulfat, A. Al Mueed and S. M. S. Reza, ―A Review on Twitter Sentiment Analysis Approaches,‖ in 2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD), Dhaka, 2021.
11. C. Perez and S. Karmakar, ―An NLP-assisted Bayesian time-series analysis for prevalence of Twitter cyberbullying during the COVID-19 pandemic,‖ Social Network Analysis and Mining, vol. 13, p. 51, 2023.
12. R. Patil, N. Gada and K. Gala, ―Twitter data visualization and sentiment analysis of article 370,‖ in 2019 International Conference on Advances in Computing, Communication and Control (ICAC3), 2019.
13. E. Najjar and S. Al-augby, ―Sentiment analysis combination in terrorist detection on Twitter: A brief survey of approaches and techniques, ‖ in Research in Intelligent and Computing in Engineering: Select Proceedings of RICE 2020, 2021.
14. K. T. Mursi and others, ―Detecting Islamic radicalism Arabic tweets using natural language processing, ‖ IEEE Access, vol. 10, p. 72526–72534, 2022.