



Machine Learning-based Sentiment Analysis of Twitter Data on the Russia-Ukraine Conflict

Gopal D. Upadhye,^{1,*} Shital P. Dongre,¹ Jyoti Kanjalkar,² Sheetal Phantangare,³ Rakhi Bhardwaj³ and Rohit Gurav¹

Abstract

The Russia-Ukraine conflict has emerged as a focal point of global discourse, with Twitter serving as a significant platform for real-time public sentiment expression. In this study, sentiment analysis techniques applied to Twitter data regarding the Russia-Ukraine conflict are explored, with machine learning models employed to derive insights. This study compares the efficacy of Bag-of-Word and term frequency-inverse document frequency (TFIDF) feature engineering strategies using a bespoke dataset of 87,547 tweets and a regular Kaggle dataset of 43,398 tweets. Accuracy, precision, recall, and F1 score measures are used to assess seven machine learning models: gradient descent classifier, stochastic decision forest classifier, binary split classifier, margin maximization classifier, probability distribution classifier, and sigmoid regression classifier. The analysis reveals TF-IDF, particularly in conjunction with the decision tree classifier, as a promising approach for sentiment analysis on Twitter concerning the Russia-Ukraine conflict. These findings contribute to understanding sentiment dynamics and provide valuable insights for future research in this domain.

Keywords: Sentiment analysis; Twitter data; Decision tree classifier; Machine learning models; Comparative analysis.

Received: 25 March 2025; Revised: 23 July 2025; Accepted: 06 August 2025

Article type: Original research.

1. Introduction

The Russia-Ukraine conflict, an ongoing saga of geopolitical tension and military confrontation, has entrenched itself as a focal point of global concern. Stemming from the annexation of Crimea in 2014, the conflict has evolved into a protracted struggle, marked by territorial disputes, armed clashes, and humanitarian crises. Its ripple effects have been felt far beyond the borders of the two nations, shaping international relations, influencing regional stability, and profoundly impacting the lives of millions caught in its crossfire. From the bustling streets of Kyiv to the war-torn landscapes of Donetsk and Luhansk, the conflict has exacted a heavy toll on civilian populations, leaving behind a trail of shattered communities, displaced families, and shattered dreams. In the digital age,

social media platforms have emerged as potent instruments for shaping public discourse and amplifying voices in times of crisis. Twitter, with its real-time nature and global reach, has become a digital battleground where narratives clash, information spreads like wildfire, and sentiments flare amidst the chaos of conflict. For individuals trapped in conflict zones, Twitter serves as a lifeline, offering a platform to document their experiences, seek assistance, and connect with the outside world. Consider the case of Anna, a resident of Mariupol, who took to Twitter to share her harrowing account of surviving a bombing raid on her neighbourhood. Her tweet, accompanied by a photo of her bloodied hands clutching her infant daughter, went viral, sparking outrage and calls for action from around the world. Similarly, the hashtag #DonetskUnderFire trended globally, as residents of the besieged city chronicled their struggles to survive amidst relentless shelling and shortages of food and medical supplies. In the realm of academia and data science, researchers have sought to harness the power of machine learning and sentiment analysis to glean insights from the vast troves of Twitter data pertaining to the Russia-Ukraine conflict. By analyzing patterns of language, sentiment, and engagement, researchers can discern underlying trends,

¹Department of Artificial Intelligence and Data Science, Vishwakarma Institute of Technology, Pune, Maharashtra, 411037, India

²Department of CSE (Artificial Intelligence and Machine Learning), Vishwakarma Institute of Technology, Pune, Maharashtra, 411037, India

³Department of Computer Engineering, Vishwakarma Institute of Technology, Pune, Maharashtra, 411037, India

*Email: gopal.upadhye@vit.edu (G. D. Upadhye)

Table 1: Dataset used.

Date	Content	Reply Count	Retweet Count	Like Count	Language	Source Label	Search
5/3/2022	Stewart: Tragic to see these civilians being targeted.	0	0	0	en	Twitter Web App	Russian troops
5/3/2022	As I said earlier, this map is not valuable information.	0	0	3	en	Twitter Web App	Russian troops
5/3/2022	This is how the USA and Britain invade a country.	1	1	4	en	Twitter for Android	Russia invades
5/3/2022	Thank you to the worker at Israel's Ben Gurion Airport.	0	1	3	en	Twitter Web App	Stand With Ukraine
5/3/2022	Playing Katarina Gryvul – No pain. #StandWithUkraine	4	1	7	en	Tweet Deck	Stand With Ukraine
5/3/2022	At this point, we need to invade Russia. Putin will not stop.	3	1	0	en	Twitter Web App	Russia invades
5/3/2022	If Biden had stressed, Ukraine would not join NATO	0	0	0	en	Twitter Web App	Russian border Ukraine
5/3/2022	Her dog is strapped to her back. #StandWithUkraine	2	19	52	en	Twitter for iPhone	Stand With Ukraine
5/3/2022	Disguise some A-10 Warthogs as MiG-29s and reach the front.	0	0	0	en	Twitter for iPhone	Russian troops
5/3/2022	Over 2M people from around the world have already donated.	0	0	0	en	Twitter for Android	Stand With Ukraine

attitudes, and emotions prevalent within the discourse.

In this study,^[1] sentiment theory applied to Twitter dataset on the Russia-Ukraine conflict was examined in many ways using different types of machine learning, including logistics regressions, polynomial naive Bayes, support vectors machine, decision trees machine, random forest classifier, additive tree classifier and gradient boosting classifier. Through rigorous evaluation and comparison of these models in the context of legal documents and procedural standards, we seek to reveal the complexity of public opinion on conflict. Beyond academic research, the implications of this research also extend to policymakers, government institutions, and humanitarian organizations responsible for addressing the various problems arising from conflict. Using insights from emotional analysis, participants can develop intervention plans, develop negative responses, and develop greater understanding as they seek solutions for peace and harmony amidst conflict and understanding. This work addresses these issues by proposing a new hybrid model that combines convolutional neural networks (CNN), short-term neural networks (LSTM), and joint learning with SVM for sentiment analysis. Our study

involves comparing eight existing machine learning models with our proposed hybrid model to demonstrate the best performance and reliability. Through rigorous analysis and comparisons, we reveal the complexity of public opinion on the conflict and provide a better understanding of strategic thinking. Information gained from emotional analysis can inform policymakers, government agencies, and humanitarian organizations working to solve problems arising from conflict. By using emotional intelligence, stakeholders can create effective plans, reduce negative impacts, and gain greater understanding when seeking compromise and resolution to disagreements. Describe the data collection and prioritization methods, the machine learning model, present the results of our comparison, and discuss the implications of our findings for study research and practical applications. The core aspect of sentiment analysis lies in classifying textual expressions based on their emotional tone — typically labelled as positive, negative, or neutral. This classification is achieved by evaluating both the semantic and syntactic characteristics of the text. Widely available datasets such as Amazon product reviews are often used to benchmark sentiment analysis

Table 2: Cleaning dataset.

Index	Tweet	Clean Text	Polarity	Subjectivity	Analysis	Label
0	Ukraine war worsens food insecurity worldwide	Ukraine war worsens food insecurity world wide report	0.0	0.0	Neutral	0
1	Sweden considers sending Ukraine Archer system	Sweden consid send Ukraine archer system Ukraine	0.0	0.0	Neutral	0
2	The Brave Ukrainians Fight Back – And We Do Absolutely Nothing...	brave ukrainian fight back absolut noth case sinc obama...	0.4	0.5	Positive	1
3	Apple heefteenboete van 2 miljoenroebelopgelegd...	applheeffteenboete van 2 miljoenroebelopgelegd...	0.0	0.0	Neutral	0
4	I'm just talking about the fauna of Donetsk region on Instagram and Facebook	im talk fauna Donetsk region Instagram Facebook	0.0	0.0	Neutral	0

algorithms because they provide large volumes of labeled sentiment-rich content, which is essential for training and evaluating supervised models. Furthermore, negative expression recognition algorithms are essential for accurately interpreting sentiment, especially in complex linguistic scenarios where negations, sarcasm, or context influence polarity. These algorithms rely on a combination of lexicon-based techniques and syntactic rules — for example, identifying terms like “not good” as negative, despite the presence of the word “good.” Tools like Text Blob and VADER incorporate these techniques to generate polarity and subjectivity scores that contribute to more nuanced sentiment classification. An important component of this research is the literature review, which summarises the body of knowledge on sentiment analysis, Twitter data analysis, and the conflict between Russia and Ukraine. Its objective is to position the study within the broader academic discourse by highlighting key concepts, methodologies, and findings. Through critical examination of prior research, the aim is to identify gaps, challenges, and opportunities, laying a solid foundation for the empirical investigation. Scholars have explored various methods to extract insights from textual data, particularly on social media like Twitter. From lexicon-based tools to machine learning techniques, approaches to decode sentiment nuances are continually innovated, enriching our understanding of public sentiment in digital discourse.^[2] Regarding the research discussed in,^[3] a general understanding of the ongoing conflict between Russia and Ukraine is provided using Twitter data and machine learning techniques. Analyzing 11,250 tweets, sentiment analysis and object labeling using natural language processing (NLP) techniques are investigated. It demonstrates the effectiveness of the learning model, especially the Extra Tree Classifier (ETC) classifier combined with the Bag of Words method, achieving an accuracy of 0.84. Logistic regression, decision trees, support vector classifier, XGBoost, Gauss Naive Bayes, AdaBoost, K nearest neighbours, *etc.* Various models explain their value in the opinion section. This study helps understand the emotional impact of social media in conflict situations and demonstrates the value of machine learning in message analysis. In this study,^[4] pioneering sentiment analysis models are developed to examine social media, particularly Twitter data, during global conflicts. Running 31,000 filtered tweets over several months, models are trained using Naive Bayes Algorithm (NBA) and Neural Networks (NN), achieving 80% and 100% accuracy, respectively. Evaluation using a confusion matrix highlights the ability of the models to classify positive and negative tweets. These findings provide valuable information for researchers and practitioners in measuring public opinion on social media platforms, especially in the midst of national conflicts, helping to better understand social responses in the digital age. The study in^[5] discusses how social media platforms like Twitter serve as spaces where users share their thoughts and connect with each other. In 2022, Twitter reported more than 206 million daily active users. Analyzing online data has become crucial for understanding changes in people’s perceptions, leading to the growing trend of sentiment analysis. This paper explores emotions about Covid-19 during England’s third lockdown using a range of methods, including vocabulary and machine learning approaches. By examining public opinion reflected in tweet data, the study provides insight into the evolution of attitudes to Covid-19 in England and offers valuable guidance for policymakers in the midst of the pandemic.

The research in^[6] examines the significance of sentiment analysis of Twitter data in capturing public opinion on social

media platforms. It emphasizes the transformative role of network technology in turning the Internet into a space for learning and opinion-sharing. This research provides a detailed and comparative overview of existing sentiment analysis techniques, focusing on machine learning and dictionary techniques. This work uses algorithms such as Naive Bayes, Maximum Entropy, and Support Vector to provide in-depth examination of sentiment in Twitter data streams. Despite significant progress, challenges remain, such as the quality of social media interactions and subtle changes in sentiment in tweets. This article highlights the importance of continued research and first steps in sentiment analysis to address these issues. The study in^[7] presents a comprehensive survey of sentiment analysis, with a special focus on the classification of sentiment polarity, a key aspect of the field. The study uses Amazon.com online product reviews as data and conducts experiments at the sentence and review levels, yielding promising results. The authors propose a general process for categorizing sentiment polarity that addresses challenges such as the unstructured nature of online opinion. In particular, the paper describes a detailed algorithm for recognizing negative expressions, a mathematical approach for calculating sentiment scores, and a feature vector generation method for sentiment polarity classification. Through extensive testing and evaluation of classification models, including performance comparisons, the study provides valuable insights into sentiment analysis. Using four well-known data mining techniques — k-nearest neighbour, decision tree classifier, support vector classifier, and naive Bayes — the study in^[8] explores sentiment on Twitter data. Two distinct sets of data were used for the experimentation: one had two groups (positive and negative), and the other had three groups (positive, negative, and neutral). Algorithms for learning are made more reliable by combining several approaches. Divide the dataset into training and testing sets using distinct datasets in order to identify the optimal training and testing sets. The findings demonstrated that SVM outperformed other methods, with accuracy increasing by 3.53% and 7.41% in the second and third data, respectively. Even if the experiment's accuracy results are somewhat better than integration's, the resulting model turns out to be more potent. Additionally, tests reveal that while training and ten-fold cross-validation produce better results, using half of the dataset as training data yields the same results as using 70% of the dataset as input. An overview of recent advancements in Twitter Sentiment Analysis (TSA) is given in the article in,^[9] which also emphasizes the significance of TSA as a current field of text mining. The TSA processes data from Twitter using computers, taking into account the subjective character of thoughts and opinions. The study

Table 3: Hybrid model.

Layer (type)	Output Shape	Param #
embedding 2 (Embedding)	(None, 100, 100)	2028700
conv1d 2 (Conv1D)	(None, 98, 128)	38528
max pooling 1d 2 (MaxPooling1D)	(None, 49, 128)	0
flatten 2 (Flatten)	(None, 6272)	0
reshape (Reshape)	(None, 49, 128)	0
lstm 2 (LSTM)	(None, 64)	49408
dense (Dense)	(None, 64)	4160
dense 1 (Dense)	(None, 3)	195
Total params: 2120991		
Trainable params: 2120991		
Non-trainable params: 0		

evaluates and categorizes the numerous algorithms and implementations put out in the subject. In order to categorize tweets into positive, negative, and neutral feelings, models for sentiment analysis on Twitter were developed in the work.^[10] Based on the results, the tree kernel-based model is the most efficient, and combining models results in higher accuracy. Most notably, it presents two indispensable tools: an acronym dictionary and a hand-annotated dictionary of emoticons. The study in^[11] presents an empirical evaluation of different preprocessing strategies and their effects on sentiment classification accuracy. It investigates how tokenization, stop-word removal, stemming, and lemmatization impact performance across various algorithms. The paper finds that a combined approach using lemmatization and n-gram modeling yields significantly better precision in short-text sentiment classification on Twitter datasets. These findings are particularly relevant for handling informal and noisy user-generated content during crisis scenarios such as the Russia-Ukraine conflict. In,^[12] researchers perform a temporal sentiment trend analysis of over 100,000 tweets related to the Russia-Ukraine conflict, aiming to detect emotional surges in response to major military or political events. Using a hybrid model combining LSTM and attention mechanisms, the study shows that spikes in public sentiment—both positive and negative—correlate strongly with key dates such as ceasefire announcements or civilian casualty reports. This temporal mapping of sentiment serves as an early-warning system for humanitarian agencies and provides deeper understanding of the emotional trajectory of populations during wartime. Finally,^[13] presents a novel ensemble model that integrates sentiment scores from multiple tools including VADER, Text Blob, and a custom CNN-based classifier. The goal is to reduce bias from single-model predictions and produce more robust sentiment scores. The ensemble method is tested against conflict-related tweet corpora and shows a 9% increase in F1 score over traditional single-algorithm models. The study also

Table 4: Results of models using BoW (Custom Dataset).

Model	Accuracy	Class	Precision	Recall	F1-Score
LR	0.95	-1	0.89	0.85	0.87
		0	0.96	0.98	0.97
		1	0.94	0.90	0.92
MNB	0.55	-1	0.28	0.60	0.39
		0	0.86	0.52	0.65
		1	0.39	0.62	0.48
SVC	0.77	-1	0.92	0.23	0.37
		0	0.75	1.00	0.86
		1	0.87	0.38	0.53
DTC	0.97	-1	0.91	0.90	0.90
		0	1.00	1.00	1.00
		1	0.93	0.94	0.94
RFC	0.90	-1	0.94	0.59	0.72
		0	0.89	1.00	0.94
		1	0.93	0.78	0.84
ETC	0.90	-1	0.94	0.61	0.74
		0	0.89	1.00	0.94
		1	0.93	0.79	0.86
GBC	0.85	-1	0.90	0.46	0.61
		0	0.83	1.00	0.91
		1	0.94	0.64	0.76

the model’s interpretability and utility for real-time monitoring of evolving public sentiment during geopolitical crises.

2. Experimentation

The research methodology section delves into the systematic approach employed to conduct the study, elucidating the methods and techniques utilized for data collection, analysis, and interpretation.^[10]

2.1 Dataset description

In this study, we leverage two distinct datasets to ensure comprehensive analysis and mitigate biases. The first dataset shown in Table 1 comprises 87,547 tweets meticulously curated to capture a diverse range of sentiments regarding the Russia-Ukraine conflict. Concurrently, we incorporate a standard dataset sourced from Kaggle, shown in Table 2, containing 43,398 tweets, to validate the robustness and generalizability of our findings. This dual-dataset approach not only enriches the scope of our analysis but also serves as a crucial validation mechanism, demonstrating the effectiveness of our sentiment analysis techniques across varying datasets.^[11] Furthermore, this study made use of two primary datasets: a custom dataset and a Kaggle dataset. Both datasets shared similar structural characteristics, comprising essential columns such as “Date,” “tweet,” “Reply Count,” “RetweetCount,” “Like Count,” “Language,” “Source Label” and “Search.” Of these, the central focus was on the “tweet” column, which contained the textual content of individual tweets. The raw

dataset functioned as the fundamental basis for the sentiment analysis carried out, enabling the retrieval of significant insights from the vast collection of user-generated content on Twitter. Fig. 1 shows the tweet representation.^[12]

2.2 System architecture

In the project’s flowchart depicted in Fig. 1, the initial phase involves data collection,^[13] where Tweepy, a Python library, and the Twitter Official Developer API are utilized to gather tweets related to the Russia-Ukraine conflict. Leveraging Tweepy’s functionalities, specific search queries and filters are constructed to target tweets pertinent to the research topic, ensuring the acquisition of a diverse and representative dataset. Simultaneously, access to a wide range of real-time Twitter data is facilitated through the Twitter Official Developer API, further enriching the dataset with relevant tweets. Upon completion of the data collection phase, the transition is made to the data preprocessing stage. Here, essential text preprocessing tasks, such as lowercasing, stemming, and removing stop words, are performed to clean and standardize the text data. Subsequently, the Python natural language processing module Text Blob is employed to ascertain the polarity and subjectivity scores of each tweet. These scores enable the measurement of sentiment and emotional tone within the message. Finally, the tweets are classified into positive, negative, or neutral sentiments based on their polarity scores.^[14] Term frequency-inverse document frequency and Bag-of-word approaches are used in the feature engineering step to extract pertinent features from the preprocessed text data.^[2] By using these methods, we are able to convert the textual data into numerical representations that accurately reflect the semantic information that lies beneath them. We next apply seven different classification models to each set of features produced by BOW and TF-IDF: logistic regression, multinomial naive bayes, support vector classifier, decision tree classifier, random forest classifier, extra trees classifier, and gradient boosting classifier. The aim is to utilize these models to categorize tweets into sentiment classes based on extracted attributes, providing an understanding of public sentiment regarding the Russia-Ukraine war.^[15] Lastly,^[16] during the evaluation process, the effectiveness of each classification model is evaluated using critical metrics such the F1 score, recall, precision, and accuracy. Furthermore, confusion matrices are produced to illustrate how well the models classify tweets into various sentiment categories. These evaluation metrics provide insightful information about how well the models reflect the subtle emotional differences in tweets about the conflict between Russia and Ukraine, helping to direct future research and decision-making.

2.3 Data collection

This study employed a comprehensive approach to data collection, utilizing the Twitter API through Tweepy to gather tweets spanning from February 22 to 2023. By leveraging various hashtags such as #russi-ukrain, #Russiainvades, and #ukrainerrussiawars, among others, the researchers filtered relevant tweets associated with the Russia-Ukraine conflict. This meticulous process resulted in a dataset comprising 87,000 tweets, providing a rich source of real-time public sentiment on the topic. Additionally, to ensure the robustness and generalizability of their models, the researchers integrated a second dataset sourced from Kaggle, which consisted of 43,000 tweets. This combination of a custom dataset and a standardized Kaggle dataset allowed for a comprehensive evaluation of sentiment analysis techniques, showcasing the effectiveness of the models across different types of datasets and reinforcing the credibility of the study's findings.^[17]

Table 5: Results of models using BoW (Kaggle).

Model	Accuracy	Class	Precision	Recall	F1-Score
LR	0.94	-1	0.87	0.84	0.87
		0	0.94	0.96	0.95
		1	0.91	0.91	0.90
MNB	0.53	-1	0.30	0.62	0.41
		0	0.85	0.50	0.61
		1	0.39	0.62	0.48
SVC	0.75	-1	0.91	0.25	0.31
		0	0.75	1.00	0.82
		1	0.85	0.39	0.51
DTC	0.95	-1	0.90	0.91	0.92
		0	1.00	1.00	1.00
		1	0.91	0.94	0.94
RFC	0.89	-1	0.93	0.58	0.70
		0	0.88	1.00	0.92
		1	0.91	0.77	0.81
ETC	0.90	-1	0.94	0.61	0.74
		0	0.89	1.00	0.94
		1	0.93	0.79	0.86
GBC	0.83	-1	0.91	0.47	0.59
		0	0.81	1.00	0.88
		1	0.91	0.66	0.78

2.4 Data preprocessing

2.4.1 Preprocessing

In this study, the preprocessing phase commenced with the removal of extraneous columns from the dataset. Irrelevant features such as retweet count, reply count, and retweet date were discarded, focusing solely on the text feature—the tweet content. By eliminating unnecessary columns, the

dataset was streamlined, ensuring that the analysis centred on the textual information essential for sentiment analysis.^[18]

Subsequently, various NLTK (Natural Language Toolkit) libraries were leveraged to perform text preprocessing tasks. Essential modules, including stop words corpus, Porter Stemmer, and word_tokenize, were imported to facilitate text manipulation operations. Additionally, necessary resources from NLTK, such as the WordNet corpus and tokenization tools, were downloaded to support advanced text processing operations. These libraries provided a robust foundation for executing the preprocessing pipeline effectively.^[19] Furthermore, a series of preprocessing steps were implemented to clean and standardize the tweet text effectively. A preprocessing function was designed to encompass key operations such as URL removal, non-alphanumeric character elimination, and conversion to lowercase. Subsequently, the cleaned text was tok-enized, stop words were removed, stemming was performed using the Porter Stemmer algorithm, and lemmatization was applied using the Word Net Lemmatize. These steps collectively transformed the raw tweet text into a refined and standardized format conducive to sentiment analysis. For instance, consider the original tweet: “The Brave Ukrainians Fight Back – And We Do Absolutly Nothing, As Has Been The Case Since Obama Under Every Democrat President #biden #putin #russia#ukraine #war.” After undergoing the preprocessing pipeline, the cleaned tweet text appeared as follows: “brave Ukrainian fight back absolut noth case sinc obama everi democrat presid biden putin russia ukrain war.” This transformed representation eliminated noise and ensured that the tweet content was optimized for sentiment analysis, enabling accurate interpretation of public sentiment regarding the Russia-Ukraine conflict.

Algorithm 1: Text Preprocessing

Require: tweet text: Text of the tweet to preprocess

Ensure: cleaned text: Preprocessed text ready for sentiment analysis

- 1: cleaned text ← ""
- 2: tweet text ← remove urls(tweet text)
- 3: tweet text ← remove non alphanumeric(tweet text)
- 4: tweet text ← convert to lowercase(tweet text)
- 5: tokens ← tokenize(tweet text)
- 6: tokens ← remove stopwords(tokens)
- 7: tokens ← apply stemming(tokens)
- 8: tokens ← apply lemmatization(tokens)
- 9: cleaned text ← join tokens(tokens)
- 10: return cleaned text

Table 6: Results of models using TF-IDF (Custom Dataset).

Model	Accuracy	Class	Precision	Recall	F1-Score
LR	0.95	-1	0.95	0.80	0.87
		0	0.94	1.00	0.97
		1	0.96	0.89	0.92
MNB	0.85	-1	0.91	0.48	0.63
		0	0.89	0.95	0.92
		1	0.72	0.80	0.76
SVC	0.96	-1	0.95	0.84	0.89
		0	0.96	1.00	0.98
		1	0.96	0.91	0.93
DTC	0.97	-1	0.88	0.88	0.88
		0	1.00	0.99	0.99
		1	0.92	0.93	0.93
RFC	0.95	-1	0.94	0.77	0.85
		0	0.95	1.00	0.97
		1	0.93	0.90	0.92
ETC	0.96	-1	0.95	0.81	0.88
		0	0.97	1.00	0.98
		1	0.93	0.94	0.93
GBC	0.85	-1	0.90	0.48	0.63
		0	0.84	1.00	0.91
		1	0.94	0.64	0.76

The preprocessing steps outlined in Algorithm 1 ensure that the raw tweet data is cleaned and standardized for analysis. Key steps include URL removal, tokenization, and lemmatization, which collectively reduce noise and improve the accuracy of sentiment classification.

2.4.2 TextBlob

In this study, sentiment analysis was carried out using TextBlob, a Python module made for processing textual data, after tweet data had been preprocessed to remove noise and standardise text format. TextBlob offers a simple API for sentiment analysis and other natural language processing (NLP) applications. The TextBlob class in TextBlob,^[20] which provides easy ways to access sentiment-related characteristics, was used to generate the sentiment ratings for every tweet. To be more precise, the polarity score—which indicates the text’s sentiment orientation—was obtained by using the sentiment.polarity attribute. This score ranges from 0 (neutral) to 1 (most positive), with -1 being the greatest negative attitude. The subjectivity score, which indicates the level of subjectivity in the text, was also extracted using the sentiment.subjectivity property. Subjectivity score: 0 represents an objective (factual) document; 1 represents a highly subjective (opinionated) piece. After each tweet’s sentiment score was obtained using TextBlob, each tweet was categorised according to its polarity score. Tweets that showed positive

sentiment were labelled as having a polarity score of +1, negative sentiment was labelled as having a score of -1, and neutral sentiment was indicated by tweets with a polarity value of 0 (showing neutral sentiment).

Algorithm 2: Labeling Tweets Based on Sentiment Score

Require: Sentiment polarity score p

Ensure: Sentiment label l

- 1: if $p > 0$ then
- 2: $l \leftarrow 1$ ▷ Positive sentiment
- 3: else if $p < 0$ then
- 4: $l \leftarrow -1$ ▷ Negative sentiment
- 5: else
- 6: $l \leftarrow 0$ ▷ Neutral sentiment
- 7: end if

Algorithm 2 categorizes tweets into positive, negative, or neutral sentiments based on polarity scores derived from TextBlob. This labeling is critical for training supervised machine learning models and evaluating their performance.

2.4.3 Data splitting

To assess the efficacy of the sentiment analysis model, the dataset was divided into training and testing sets during the data splitting phase. An 80-20 split, which assigns 80% of the data to the training set and the remaining 20% to the testing set, was used, in accordance with standard procedure. This partitioning strategy ensured the robustness and dependability of the sentiment analysis approach used in the research endeavour by facilitating a thorough evaluation of the model’s score metrics. The number of^[21] positive, negative, and neutral tweets in the dataset is displayed as below:

Comparison of the polarity distributions between the custom dataset and the Kaggle dataset is shown in Fig. 2. The custom dataset exhibits a higher frequency of neutral tweets, likely due to the inclusion of factual news updates, while the Kaggle dataset shows a more balanced distribution of positive and negative sentiments. This difference may stem from variations in data collection methods or the time periods covered by each dataset.

2.5 Feature engineering

Two different feature engineering strategies were used in this study: term frequency-invert document frequency and Bags-of-Word. BoW disregards word order and structure and instead depicts text data as a matrix of word occurrences. On the other hand, TF-IDF highlights the importance of uncommon terms by allocating weights to words depending on how frequently they occur in a document in comparison to how frequently they occur throughout the entire corpus. These techniques make it possible to convert textual data into numerical vectors, which

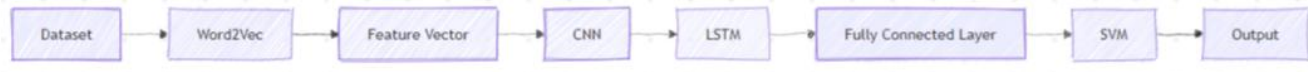


Fig. 1: Flow chart of proposed model.

makes it easier to use that data as input for machine learning models.^[22] After these feature engineering techniques were used, an evaluation was carried out to determine which machine learning models performed best on the preprocessed data. Finding out how well these models performed in relation to each feature engineering technique was the goal.^[23]

2.6 Machine learning models

In the context of the Russia-Ukraine war, this study thoroughly evaluates seven different machine learning models for sentiment analysis. The logistic regression, multinomial naive Bayes, support vector, decision tree, random forest, additional trees, and gradient boosting classifiers are among the models that were selected. Two feature engineering strategies, bags-of-word and term frequency-inverse document frequency, were applied separately to each model^[24]

- **Logistic Regression:** A linear model suitable for binary classification tasks, Logistic Regression estimates probabilities using a logistic function.

- **Multinomial Naive Bayes:** Based on Bayes’ theorem, this model assumes independence between features and is commonly used for text classification tasks.

- **Support Vector Classifier:** Effective in high-dimensional spaces, Support Vector Classifier constructs hyperplanes to separate data points into different classes.

- **Tree-based classifier (decision):** Tree Classifier is a non-parametric model that divides the data into sub-groups recursively using feature splits and offers comprehensible classification rules.

- **Ensemble tree classifier(random):** a method of ensemble learning that reduces overfitting and increases precision by constructing many decision trees and aggregating the results.

- **Extra Trees Classifier:** Similar to Random Forests, Extra Trees Classifier builds multiple decision trees on random subsets of the data and features to enhance generalization.

- **Boosted trees classifier:** Gradient Boosting Classifier is a boosting technique that uses gradient descent to minimise mistakes iteratively while combining weak learners in order to increase predictive performance.

The chosen algorithms are tailored to the task,^[25] each bringing distinct advantages. Logistic Regression offers simplicity and efficiency in binary classification. Multinomial classifiers ideal for text classification, assuming feature

independence. Support Vector Classifier excels in high-dimensional data and nonlinear tasks. Decision Tree Classifier ensures interpretability and captures intricate data relationships. Random Forest and Extra Trees Classifier employ ensemble learning for enhanced performance. Gradient Boosting Classifier iteratively refines model accuracy through weak learner integration.^[19] By running these models on both BoW and TF-IDF features separately, this study aims to compare their performance and discern any variations in results. The diverse nature of these algorithms, coupled with the distinct characteristics of BoW and TF-IDF, is expected to yield differing outcomes. Such variations will be further analyzed and discussed in the subsequent sections, providing valuable insights into the effectiveness of each feature engineering technique and machine learning model combination.^[26]

Table 7: Results of models using TF-IDF (kaggle dataset).

Model	Accuracy	Class	Precision	Recall	F1-Score
LR	0.92	-1	0.93	0.75	0.83
		0	0.91	0.99	0.95
		1	0.94	0.86	0.89
MNB	0.81	-1	0.87	0.41	0.57
		0	0.84	0.94	0.89
		1	0.72	0.78	0.75
SVC	0.93	-1	0.94	0.77	0.88
		0	0.92	1.00	0.96
		1	0.94	0.87	0.90
DTC	0.95	-1	0.89	0.86	0.87
		0	0.98	0.99	0.99
		1	0.91	0.91	0.91
RFC	0.93	-1	0.94	0.77	0.85
		0	0.93	1.00	0.96
		1	0.93	0.87	0.90
ETC	0.94	-1	0.95	0.80	0.87
		0	0.97	0.99	0.95
		1	0.93	0.92	0.92
GBC	0.85	-1	0.91	0.56	0.69
		0	0.82	1.00	0.90
		1	0.94	0.68	0.79

2.7 Evaluation measures

In^[27] evaluating the performance of sentiment analysis models, a comprehensive set of metrics is employed, including

accuracy, F1 score, recall, precision, and confusion matrix analysis. These metrics provide a holistic understanding of each model’s effectiveness in classifying sentiment across the dataset. In this study, the performance of seven sentiment analysis models—linear classifier, naive Bayes classifier, SVM classifier, tree-based classifier, ensemble tree classifier, extremely randomized trees classifier, and boosted trees classifier—is rigorously evaluated using these evaluation measures. Through meticulous comparison and analysis, the study aims to identify the most effective model for sentiment analysis tasks concerning the Russia-Ukraine conflict on Twitter data.^[28]

2.8 Proposed model

The suggested model architecture for sentiment analysis is depicted in the Fig. 3. First, word embeddings are created from the dataset using the Word2vec technique. Then, by using these embeddings, feature vectors are produced that extract semantic information from the input data. Following this, CNN layer sequentially processes the feature vectors in order to extract pertinent spatial characteristics. A LSTM network is then fed the CNN layer’s output, allowing the model to recognise temporal dependencies in the data. The output of the LSTM layer is then transferred through fully connected layers, which makes feature representation and higher-level abstraction possible. The ultimate outcome of the sentiment analysis process is a SVM classification of the feature representation. The LSTM and CNN model parameters utilised in the investigation are presented in detail in the accompanying table. Recent advancements in deep learning have shown the effectiveness of hybrid architectures in sentiment analysis, particularly models combining CNN for spatial feature extraction and LSTM for sequential understanding. In our proposed hybrid model, the CNN component captures local n-gram patterns in the Word2Vec-generated embeddings, which are then passed to an LSTM layer for temporal learning. This design choice aligns with the methodology proposed by Khan *et al.*,^[30] who demonstrated the superiority of convolutional neural

networks in text classification tasks through hierarchical feature learning. Their work further validates the inclusion of CNN layers prior to temporal sequence models in sentiment classification pipelines. The initial layer of the hybrid model, the Convolutional Neural Network (CNN), is in charge of processing the vector that the word embeddings produce. It features 128 filters and a single convolutional layer with a kernel size of three. This layer receives the data, processes it, and then sends it to the deep learning layer below. After the CNN, the model has an LSTM layer that generates a 1×64 matrix that serves as the classifier’s input. The hybrid model’s classifier is then composed of two 64-node continuous fully linked layers. Last but not least, the output layer employs a Softmax activation function to aid in the model’s precise sentiment classification. The proposed hybrid model is represented by following Table 3 as a hybrid model as given follows:

Table 8: Hybrid model results.

Evaluation	SVM	CNN	LSTM	Hybrid
Accuracy	0.96	0.90	0.82	0.90
F1	0.93	0.87	0.89	0.85
Recall	0.84	0.87	0.84	0.89
Precision	0.96	0.92	0.94	0.91
Cach N. Dang (Accuracy)	0.82	0.87	0.86	0.89
Cach N. Dang (F1)	0.82	0.86	0.89	0.88
Cach N. Dang (Recall)	0.80	0.85	0.81	0.91
Cach N. Dang (Precision)	0.84	0.87	0.86	0.86

3. Results and discussion

Using tweepy, a Python natural language processing library, to extract tweets from the gathered data was the first step in creating the “custom dataset.” Lexical analysis was then carried out with TextBlob. After that, training and testing sets were created from the dataset. Following the use of feature engineering strategies, such as weighted word frequency representation and word frequency representation, several machine learning models were applied in order to evaluate

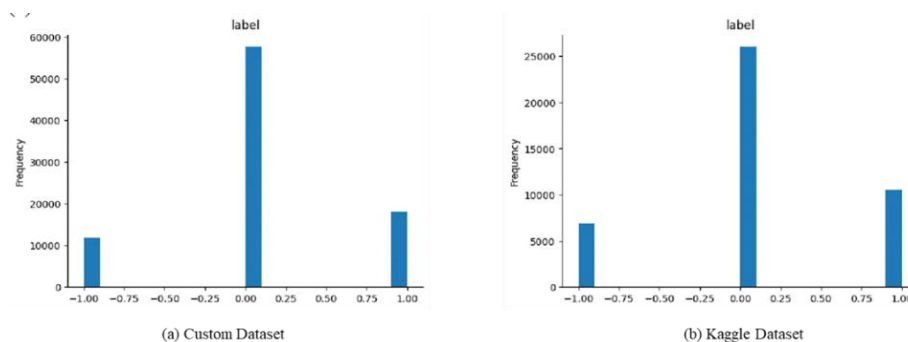


Fig. 2: Comparison of polarities vs frequencies in (a) Custom Dataset (b) Kaggle dataset.

each feature engineering approach’s performance. The analysis and results that followed are outlined below.

3.1 Results using bag of words (BoW)

Following the experimentation conducted on the custom dataset using Bag of Words (BoW) shown in Table 4 and Kaggle dataset shown in Table 5, the accuracy values for each machine learning model were determined. The results are as follows: Logistic Regression (LR) achieved an accuracy of 95%, Support Vector Classifier (SVC) attained 77%, Multinomial Naive Bayes (MNB) reached 55%, Decision Tree Classifier (DTC) demonstrated the highest accuracy at 97%, Random Forest Classifier (RFC) achieved 90%, Gradient Boosting Machine (GBM) obtained 85%, and Extra Trees Classifier (ETC) yielded 90%. Notably, the Decision Tree Classifier (DTC) emerged as the top-performing model, achieving the highest accuracy of 97%. Conversely, Multinomial Naive Bayes (MNB) exhibited the poorest performance, with an accuracy of 55%.

3.2 Results using term frequency-inverse frequency (TF-IDF)

The accuracy values for each machine learning model were ascertained by utilising the TF-IDF feature engineering method to execute tests on the custom dataset shown in Table 6 and Kaggle dataset shown in Table 7. The following outcomes were attained: The following classifiers have different percentages: 96% for SVM, 97% for tree-based, 97% for ensemble, 95% for randomised trees, 96% for extremely randomised trees, 85% for boosted trees, and 95% for linear. Remarkably, the best accuracy score of 97% was attained by

both the tree-based classifier (dtc) and the much randomised trees classifier (etc.), demonstrating their efficacy in sentiment analysis. On the other hand, with respective scores of 85%, the boosted trees classifier (gbc) and the Naive Bayes classifier (mnb) showed the lowest accuracy. These scores are nonetheless impressive despite being lower, demonstrating the models’ resilience to various feature engineering strategies. The effectiveness of many machine learning models in sentiment analysis was assessed after testing on a bespoke dataset utilising Bag of Words (BoW) and term frequency-inverse frequency (TF-IDF) feature building techniques. Logistic Regression (LR) achieved 95% accuracy with BoW, and Decision Tree Classifier (DTC) was the best-performing model with 97% accuracy. Multinomial Naive Bayes (MNB), on the other hand, showed the lowest accuracy at 55%. High accuracy scores ranging from 95% to 97% were attained by using TF-IDF, SVM, tree-based classifiers, and ensemble approaches; both DTC and Extra Trees Classifier (ETC) obtained 97%. Notably, accuracy was lower at 85% for the Boosted Trees Classifier (GBC) and MNB. All of the models and feature engineering techniques showed resilience and efficacy in sentiment analysis, despite variations in performance.

3.3 Results for proposed hybrid model

The hybrid deep learning model’s evaluation metrics and outcomes are shown in the Table 8. The model performs better than the standard paper written by Cach N. Dang, as demonstrated by the comparisons made, especially with regard to accuracy. Notably, the model outperforms the published accuracy in the reference work in every assessment criterion,

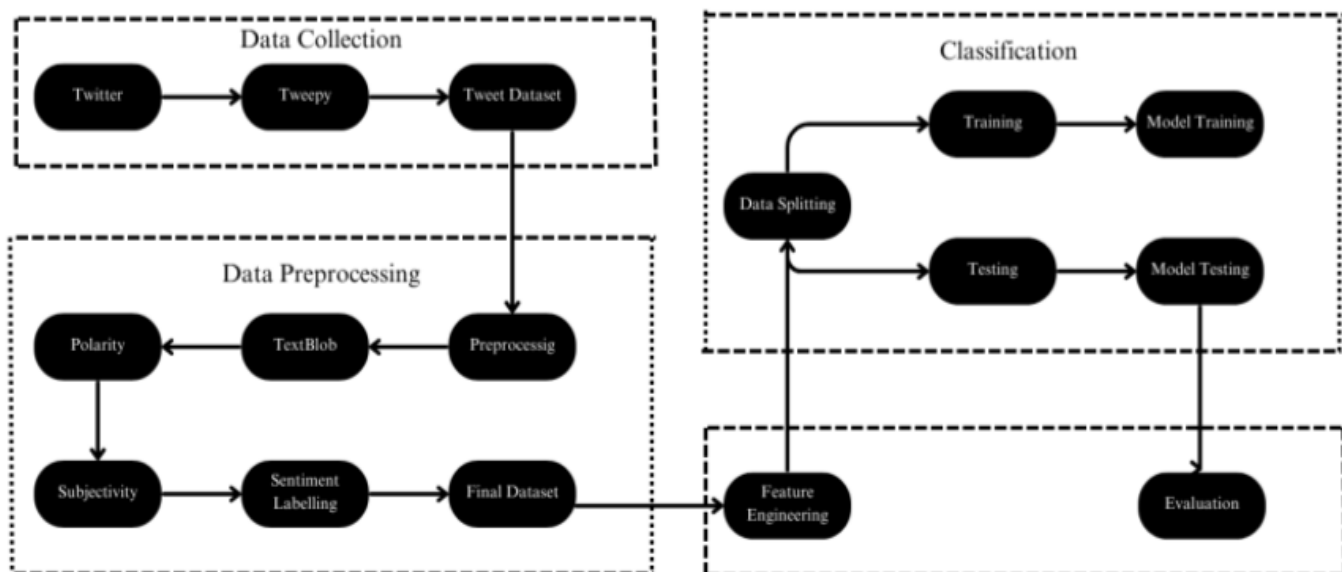


Fig. 3: Proposed system architecture.

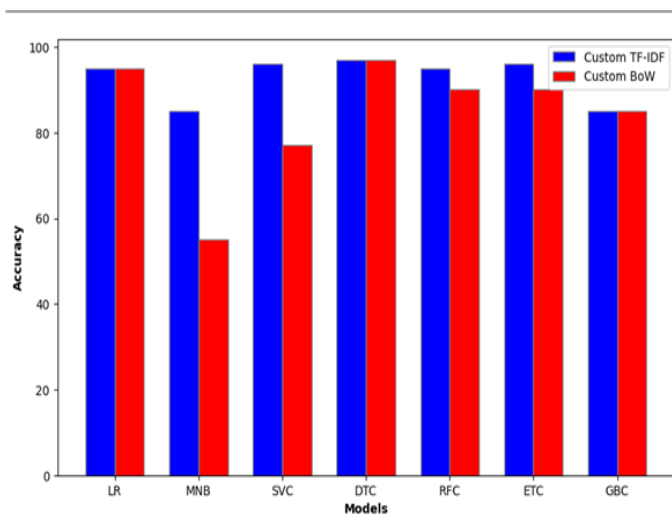


Fig. 4: Comparative analysis of BoW and TF-IDF.

highlighting its resilience and effectiveness in sentiment analysis assignments.^[29] To contextualize the performance of our hybrid CNN-LSTM-SVM model, we examined its design against recent developments in machine learning-based mediation models. For instance, the study by Zhang *et al.*^[31] applies mediation analysis to structured survey data to predict mental health outcomes, focusing on relationships between psychosocial variables. Their model architecture prioritizes interpretability and causal inference through intermediary variables. In contrast, our approach is designed for dynamic sentiment prediction using unstructured, real-time social media data. While mediation models like those in are optimized for causal discovery in health informatics, our model emphasizes representational learning and classification robustness over noisy linguistic patterns. Unlike structured input with predefined variables, our pipeline processes vast textual variability using embeddings (Word2Vec), convolutional layers (CNN) for spatial feature capture, and LSTM for sequential context — followed by SVM for optimized decision boundaries. Notably, mediation models focus on mediators and moderators affecting an outcome, whereas our model performs end-to-end sentiment classification without predefined causal assumptions. This distinction highlights the flexibility of our architecture in rapidly evolving crisis scenarios such as the Russia-Ukraine conflict, where the volume, velocity, and variability of public sentiment cannot be adequately captured by survey-based or static mediation designs. This comparison highlights the progress made by combining SVM, LSTM networks, and CNN in the hybrid model to produce improved sentiment analysis results. A recent study by proposed a novel Gate Control Unit-Recurrent Neural Network (GCU-RNN) structure for audio-based sentiment analysis, achieving significant improvements in accuracy and robustness.^[32] While

their work focused on audio data, the principles of hybrid neural network architectures align with our approach of combining CNN, LSTM, and SVM for text-based sentiment analysis. Their findings underscore the potential of advanced neural structures in capturing nuanced sentiment patterns, which could be adapted for Twitter data analysis in future work. At the last Fig. 4. Comparative analysis of BoW and TF-IDF for different machine learning algorithms. Gate Control Unit-Recurrent Neural Network (GCU-RNN) structure for audio-based sentiment analysis, achieving significant improvements in accuracy and robustness.^[32] While their work focused on audio data, the principles of hybrid neural network architectures align with our approach of combining CNN, LSTM, and SVM for text-based sentiment analysis. Their findings underscore the potential of advanced neural structures in capturing nuanced sentiment patterns, which could be adapted for Twitter data analysis in future work.

4. Conclusion

In summary, this study used both the custom dataset and the standard Kaggle dataset to examine the performance of seven different machine learning models: the linear classifier, naive Bayes classifier, SVM classifier, tree-based classifier, ensemble tree classifier, extremely randomised trees classifier, and boosted trees classifier. There were notable differences in model accuracies when using the TF-IDF feature engineering approach on the custom dataset. With the highest accuracy of 97%, the tree-based classifier (dtc) and extremely randomised trees classifier (etc) were closely followed by the SVM classifier (svc) and ensemble tree classifier (rfc), with 96% and 95% accuracy, respectively. On the other hand, 85% accuracy was shown by the boosted trees classifier (gbc) and the naive Bayes classifier (mnb). When the models were tested using TF-IDF on the standard Kaggle dataset, the tree-based classifier (dtc) yielded the highest accuracy (95%), followed by the extremely randomised trees classifier (etc) (94%). With accuracies of 92% and 93%, respectively, SVM classifier (SVC) and logistic regression (LR) also fared well. Out of all the models, the Naive Bayes classifier (mnb) produced the least accurate results, at 81%. Different patterns were seen after bag-of-words (BoW) feature engineering was used to assess the performance of the seven machine learning models on both the custom and standard Kaggle datasets. With a 97% accuracy rate on the custom dataset, the tree-based classifier (dtc) outperformed logistic regression (lr) and ensemble tree classifier (rfc), which had 95% and 90% accuracy rates, respectively. While the boosted trees classifier (gbc) and the extremely randomised

trees classifier (etc) produced accuracies of 85% and 90%, respectively, the SVM classifier (svc) achieved an accuracy of 77%. The Naive Bayes classifier (mnb) achieved an accuracy of 55%, which was a pretty low performance. Comparing the results obtained from BoW and TF-IDF feature engineering techniques, it is evident that TF-IDF consistently outperformed BoW across all models and datasets. This suggests that TF-IDF feature engineering is more effective in capturing the sentiment of the text data than BoW. Also, the hybrid model shown in paper shows its capability to analyze the data is much higher than standard methods. Additionally, the Decision Tree Classifier (DTC) emerged as the most robust model for sentiment analysis, irrespective of the feature engineering technique employed.

Acknowledgments

This work is original research work and not funded by any organization. All the authors and contribution of all this research work.

Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

CRedit Statement

Gopal D. Upadhye: Conceptualization, Methodology. **Shital P. Dongre:** Dataset creation. **Jyoti Kanjalkar:** Visualization, Investigation. **Sheetal Phatangare:** Supervision. **Rakhi Bhardwaj:** Software, Validation. **Rohit Gurav:** Writing, Reviewing and Editing, Original draft preparation.

References

- [1] Darshan, K., Samuel, J., Manjunatha Swamy, C., Koparde, P., and Shivashankara, N. NLP-Powered Sentiment Analysis on Twitter, *Saudi Journal of Engineering and Technology*, 2024, 9(1), 1–11, doi: 10.36348/sjet.2024.v09i01.001.
- [2] F. Zamani, S. A. Halim, S. Mutalib, S. B. Yusoff, Public sentiment of biodiversity conservation using machine learning approach, *IEEE International Conference on Computing (ICOCO)*, Langkawi, Malaysia, October 9-12, 2023, 182-187, doi: 10.1109/ICOCO59262.2023.10397822.
- [3] G. K. Wadhvani, P. K. Varshney, A. Gupta, S. Kumar, Sentiment analysis and comprehensive evaluation of supervised machine learning models using twitter data on Russia–Ukraine war, *SN Computer Science*, 2023, 4, 346, doi: 10.1007/s42979-023-01790-5.
- [4] S. H. Sumantri, S. Maarif, B. A. Yulianto, A. H. Sutawijaya, the influence of corporate strategy, on environmental management implications for decision making: a survey of all communities affected by landslides as due to environmental damage in nganjuk regency, *International Review of Management and Marketing*, 2019, 9, 57-65, doi: 10.32479/irmm.8552.
- [5] Shekhar, S. Text mining and sentiment analysis, *International Research Journal of Engineering and Technology (IRJET)*, 2021, 8(1), 282–290.
- [6] U. Sasikumar, A. Zaman, A.-R. Mawlood-Yunis, P. Chatterjee, Sentiment analysis of twitter posts on global conflicts, *International Conference on Computational Science and Computational Intelligence (CSCI)*, Las Vegas, NV, USA, IEEE, December 13-15, 2023, 759-764, doi: 10.1109/CSCI62032.2023.00129.
- [7] V. Sahayak, V. Shete, and A. Pathan, Sentiment analysis on twitter data, *International Journal of Innovative Research in Advanced Engineering (IJRAE)*, 2015, 2(1), 178–183.
- [8] F. Rustam, A. Mehmood, M. Ahmad, S. Ullah, D. M. Khan, G. S. Choi, Classification of shopify app user reviews using novel multi text features, *IEEE Access*, 2020, 8, 30234-30244.
- [9] Agarwal, A., Xie, B., Vovsha, I., Rambow, O., and Passonneau, R. Sentiment Analysis of Twitter Data, *Proceedings of the Workshop on Language in social media (LSM)*, 2011, 30–38.
- [10] Y. M. Wazery, H. S. Mohammed, E. H. Houssein, Twitter sentiment analysis using deep neural network, *14th International Computer Engineering Conference (ICENCO)*, Cairo, Egypt, IEEE, December 29-30, 2018, 177-182, doi: 10.1109/ICENCO.2018.8636119.
- [11] H. A. Shehu, M. H. Sharif, M. H. U. Sharif, R. Datta, S. Tokat, S. Uyaver, H. Kusetogullari, R. A. Ramadan, Deep sentiment analysis: a case study on stemmed Turkish twitter data, *IEEE Access*, 2021, 9, 56836-56854. doi: 10.1109/ACCESS.2021.3071393.
- [12] R. D. Desai, Sentiment analysis of twitter data, *Second International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, IEEE, June 14-15, 2018, 114-117, doi: 10.1109/ICCONS.2018.8662942.
- [13] M. Bouazizi, T. Ohtsuki, A pattern-based approach for multi-class sentiment analysis in twitter, *IEEE Access*, 2017, 5, 20617-20639.
- [14] M. Bouazizi, T. Ohtsuki, Multi-class sentiment analysis in twitter: what if classification is not the answer, *IEEE Access*, 2018, 6, 64486-64502.
- [15] J. Zhao, X. Gui, Comparison research on text pre-processing methods on twitter sentiment analysis, *IEEE Access*, 2017, 5, 2870-2879.

- [16] J. Zhao, X. Gui, X. Zhang, Deep convolution neural networks for twitter sentiment analysis, *IEEE Access*, 2018, **6**, 23253-23260.
- [17] M. Kanakaraj, R. M. R. Guddeti, NLP based sentiment analysis on Twitter data using ensemble classifiers, *3rd International Conference on Signal Processing, Communication and Networking (ICSCN)*, Chennai, India, IEEE, March 26-28, 2015, 1-5, doi: 10.1109/ICSCN.2015.7219856.
- [18] S. E. Saad, J. Yang, Twitter sentiment analysis based on ordinal regression, *IEEE Access*, 2019, **7**, 163677-163685. doi: 10.1109/ACCESS.2019.2952127.
- [19] M. AminiMotlagh, H. Shahhoseini, N. Fatehi, A reliable sentiment analysis for classification of tweets in social networks, *Social Network Analysis and Mining*, 2022, **13**, 7, doi: 10.1007/s13278-022-00998-2.
- [20] Y. Qi, Z. Shabrina, Sentiment analysis using twitter data: a comparative application of lexicon- and machine-learning-based approach, *Social Network Analysis and Mining*, 2023, **13**(1), 31, doi: 10.1007/s13278-023-01030-x.
- [21] S. S. Patil, A. A. Patil, S. B. Bamane, S. S. Karajgar, S. M. Sankpal, and A. P. Budaragade, Sentimental analysis, ResearchGate, 2023.
- [22] V. Kharde, P. Sonawane, *et al.*, Sentiment analysis of twitter data, a survey of techniques, arXiv, preprint arXiv:1601.06971, 2016.
- [23] A. Alsaeedi, M. Zubair, A study on sentiment analysis techniques of twitter data, *International Journal of Advanced Computer Science and Applications*, 2019, **10**(2), 361-374, doi: 10.14569/ijacsa.2019.0100248.
- [24] X. Fang, J. Zhan, Sentiment analysis using product review data, *Journal of Big Data*, 2015, **2**, doi: 10.1186/s40537-015-0015-2.
- [25] R. Gurav, S. Suryawanshi, P. Narkhede, S. Patil, S. Hukare, and K. Vayadande, Universal turing machine simulator, *International Journal of Advance Research, Ideas and Innovations in Technology*, 2022, **8**(1), 541-245.
- [26] P. Bailke, R. Gurav, S. Suryawanshi, P. Narkhede, S. Hukare, S. Patil, Personalized travel recommendation system: Hybrid model based on ratings and image analysis, *4th International Scientific Conference of Alkafeel University (Iscku 2022)*, Najaf, Iraq, AIP Publishing, 2023, 030002, doi: 10.1063/5.0181493.
- [27] K. Vayadande, R. Gurav, S. Patil, S. Chavan, V. Patil, A. Thorat, Wildfire smoke detection using faster R-CNN, *Proceedings of the Second International Conference on Computing, Communication, Security and Intelligent Systems*, Singapore, Springer Nature Singapore, 2024, 141-164, doi: 10.1007/978-981-99-8398-8_10.
- [28] S. M. Mazharul Hoque Chowdhury, P. Ghosh, S. Abujar, M. Arina Afrin, S. Akhter Hossain, Sentiment analysis of tweet data: the study of sentimental state of human from tweet text, *Emerging Technologies in Data Mining and Information Security*, Singapore, Springer Singapore, 2018, 3-14, doi: 10.1007/978-981-13-1498-8_1.
- [29] C. N. Dang, M. N. Moreno-García, F. De la Prieta, Hybrid deep learning models for sentiment analysis, *Complexity*, 2021, 9986920, 16, doi: 10.1155/2021/9986920.
- [30] N. Siddiqui, Creating deep convolutional neural networks for image classification, *Programming Historian*, 2023, doi: 10.46430/phen0108.
- [31] X. Zhang, A. Wang, J. Li, *et al.*, Predicting Mental Health Outcomes Using Machine Learning-Based Mediation Models, *BMC Public Health*, 2024, doi: 10.2174/0117450179315688240607052117.
- [32] S. Thimmaiah, R. Jayaram, A new gate control unit-recurrent neural network structure for audio-based sentiment analysis, *Engineered Science*, 2024, **30**, 1180, doi: 10.30919/es1180.

Publisher's Note: Engineered Science Publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access

This article is licensed under a Creative Commons Attribution 4.0 International License, which permits the use, sharing, adaptation, distribution and reproduction in any medium or format, as long as appropriate credit to the original author(s) and the source is given by providing a link to the Creative Commons license and changes need to be indicated if there are any. The images or other third-party material in this article are included in the article's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this license, visit <http://creativecommons.org/licenses/by/4.0/>.

© The Author(s) 2025.