Feature Selection and Sentiment Analysis Using a Hybrid Machine Learning Model

Aman Kaushik, Maitreyee Dutta
National Institute of Technical Teacher Training and Research (NITTTR), Chandigarh

Abstract**—**The sentiment analysis technique that applies natural language processing (NLP) to classification is called opinion mining. A variety of web data can be used to analyze sentiments. Machine learning refers to the classification techniques that are employed. In earlier studies, tokenization was used to implement sentiment analysis, which is less effective than machine learning. Machine learning techniques are employed in this study to analyze the sentiment of real-time Twitter data. A number of procedures are used to analyze the feelings, including pre-processing, attribute extraction, and eventual data categorization. Fraud detection efficiency was increased, noise was decreased, and predictive performance was improved using the hybrid combination of Random Forest and Logistic Regression. In addition to detection, the proposed framework aids insurers in better underwriting, risk assessment, and cost control.

Keywords—Sentiment analysis, Random Forest, Logistic Regression, Feature Selection

I. INTRODUCTION

The enormous volume of real-time thoughts communicated on Twitter has led to the rise of sentiment analysis as a major area of research. On the microblogging social media platform Twitter, users submit quick messages known as tweets that express their thoughts on a range of subjects, including politics, products, entertainment, and social issues [1][2]. With their potential to include text, hashtags, emojis, videos, and photographs, these tweets provide valuable information on public sentiment. Since millions of tweets are produced daily, Twitter has a wealth of unstructured data that may be mined to uncover user patterns, viewpoints, and emerging issues. Sorting tweets into Positive, Negative, or Neutral categories according to the information's polarity is the main goal of sentiment analysis [3][4]. Advanced NLP and AI methods, including machine and deep learning models, are used to handle and analyse this textual data. These methods support large-scale public opinion forecast, emotion detection, and pattern recognition. One of the unique challenges in analysing Twitter data is the text's informal and noisy style, which commonly contains slang, acronyms, misspellings, and context-dependent meanings [5][6]. Despite these challenges, sentiment analysis on Twitter has potential applications across a range of domains. Businesses use it for brand monitoring and consumer feedback analysis; governments and organisations use it to gauge public opinion; and researchers use it to study social, cultural, and psychological trends.

Multilingual sentiment analysis has gained popularity as Twitter's user base expands globally, making it possible to examine user sentiments outside of English-speaking areas. Twitter sentiment analysis's broader scope has made it a vital tool for both academic and industry circles, offering more comprehensive and inclusive insights into ideas throughout the world. Companies, groups, and scholars collect and analyse tweets from a range of people about specific topics. This process, which is frequently referred to as sentiment analysis, involves identifying and categorising people's opinions from their social media posts using computational methods. Because Twitter serves as a quick-reaction tool for exchanging thoughts and comments in real time, several research have specifically focused on it. The rapid growth of online content and social media participation makes sentiment analysis increasingly important, especially for companies trying to gauge public opinion [7][8]. Twitter sentiment analysis provides businesses with valuable insights into customer sentiment that aren't always available through traditional feedback channels. Compared to e-commerce sites or movie review websites, which often attract vehement comments from extremely happy or unhappy people, Twitter captures a greater variety of common opinions. This makes it a valuable instrument for gauging consumer sentiment, brand reputation, and public responses to events or items. One of the biggest challenges in sentiment analysis of Twitter data is the creation of labelled datasets. Three sentiment classes—neutral/objective statements, negative emotions, and positive emotions—are often extracted from tweets using the Twitter API. However, the unprocessed data is inherently noisy. Slang, hashtags (#topic), user mentions (@username), links, emojis, and even non-textual elements in tweets make accurate classification more challenging.

To solve these issues, a pre-processing step is applied before feature extraction and classification. The dataset must be cleaned by removing duplicates, special characters, non-English tweets, retweets, and postings that only contain URLs. These elements introduce noise and lower the accuracy of sentiment categorisation models if they are left untreated. NLP techniques such as stemming, lemmatisation, stop-word removal, tokenisation, POS tagging, and sentence segmentation are also employed. These steps normalise the textual input, reduce redundant information, and enhance the model's ability to detect important user sentiment trends. However, when working with low-resource or lower-density languages, these methods' applicability is sometimes limited due to their reliance on pre-trained language models and the availability of linguistic resources [9][10]. When such resources are few or unavailable, researchers frequently do cross-language sentiment classification using models that have previously been trained using parallel corpora or translation techniques in high density languages like English. This approach broadens the application of sentiment analysis, but it also has drawbacks, including lost contextual meaning, cultural quirks, and challenges with translation. Certain language models are employed to handle feature representation in Twitter data in order to minimise the feature space while maintaining semantic richness [11][12]. Bigrams and unigrams that exceed a preset frequency threshold are often extracted from the corpus first; for example, items or phrases that occur more than five times are selected as candidate features.

In order to identify direct relationships with sentiment-bearing utterances at the word and phrase levels, bigrams and unigrams are commonly used in sentiment analysis. This approach can also be expanded to include trigrams, which allows for the collection of more complex contextual dependencies. The frequency of each characteristic inside a single tweet is computed after the potential features have been identified. Algorithms use this feature representation as the foundation for classification models to distinguish between positive, negative, and neutral feelings based on recurring linguistic patterns across the dataset. Researchers can control and improve the dimensionality of the feature space and increase the intensity of sentiment categorisation by integrating n-gram analysis into the modelling process. The assumption that each document conveys a consistent sentiment polarity towards a certain target from a single source is a common one for sentiment researchers. This assumption holds true in contexts like product reviews, where viewpoints are usually expressed explicitly. Given the length of tweets, this assumption also holds true for Twitter data, as users tend to express their emotions succinctly and directly because of the character limits on the network. The effectiveness of sentiment classification is greatly influenced by the analytical approach taken. Lexicon methods, machine learning methods, and rule-based methods are the three main groups into which sentiment analysis techniques can be divided. Using pre-made word dictionaries that convey sentiment is a component of lexicon-based techniques [13][14]. The text is initially tokenised into distinct units using this method, and each token is subsequently compared to dictionary entries. For instance, the overall score for good mood is raised if the dictionary defines the word "dramatic" as positive. Similarly, words that are categorised as negative lower the emotion score. Despite their simplicity, lexicon-based methods are often effective, particularly in clearly defined contexts. This category includes categorisation methods such as majority voting, threshold-based document scoring, and word count-based evaluations. Corpus-based techniques and dictionary-based approaches are the two primary subcategories.

In dictionary-based methods, the initial collections of opinion words are expanded by using lexical dictionaries and often WordNet and other resources. These terms usually have limited contextual accuracy because they are domain-independent. However, by examining syntactic and statistical trends in certain contexts, corpus-based approaches find opinion terms from massive datasets, enhancing the handling of complex, domain-dependent attitudes. An alternative that is more flexible is machine learning, which uses algorithms to extract sentiment patterns from data. The basic idea is to train a model on datasets to find important linguistic patterns that may be used to categorise text that hasn't been viewed yet. Both supervised and unsupervised methods for machine learning are possible [15][16]. The most popular supervised learning algorithms for sentiment analysis are Naive Bayes, SVM, and RF because of their exceptional ability to categorise the intensity of sentiment polarities. They do, however, require huge labelled datasets, which are frequently costly and challenging to acquire. Contrarily, unsupervised techniques function without labelled data, which makes them helpful in situations when annotated datasets are not accessible, albeit they are typically less accurate. Finding patterns that generalise successfully so that the models can accurately predict sentiment in new data is the aim in both situations. Rule-based methods use a collection of rules that are either automatically produced or created by humans to categorise text. Typically, a rule has a corresponding class label on the right side and requirements stated in terms of feature presence on the left. Since the lack of words has less discriminative value, particularly in situations with sparse data, like tweets, these rules frequently highlight the presence of particular terms. Measures like support—the absolute number of examples that satisfy a rule—and confidence—the likelihood that a classification is accurate when the rule applies—are frequently used in rule creation during training. VADER, a model created especially for sentiment analysis on microblogging sites like Twitter, is a well-known example. VADER is especially useful for short, informal, and context-rich texts because it combines a variety of lexical features and rule-based heuristics to produce more reliable results than traditional lexicon-only or straightforward rule-based techniques.

II. Literature Review

M. bredice et al. (2025) investigated the association between new fintech businesses and credit availability during and after the COVID-19 pandemic using three distinct lexicon-based sentiment analyses using the NLTK, TextBlob, and Flair Python libraries [17]. Previously, they used a variety of key word combinations in the scraper script to collect data on Twitter (now known as X). They focused on the best possible combination of phrases. In order to demonstrate if the findings applied to the continents in question, they also offered an empirical estimate. Even if there was a minor drop in the quantity of tweets using the terms "access to credit" and "fintech" at the end of the coronavirus epidemic, they have gained valuable information on a continental level regarding the change in mood over the examined period.

A. Ba Alawi et al. (2024) suggested a Turkish text sentiment analysis process that used deep learning methods, nine traditional machine learning frameworks, and BERT-based transformers based on 17,793 Turkish tweets that were personally assessed to determine the level of satisfaction with Turkish universities [18]. Even during testing, the model showed remarkable accuracy of over 0.9101, an F1 Score of 0.8801, and a ROC of 0.9632 for sentiment analysis, outperforming the most sophisticated models and proving its capacity to manage the linguistic complexity of Turkish sentiment analysis.

B. Valarmathi et al. (2024) centred on sentiment analysis of COVID-19-related data on Twitter using the Long Short-term Memory (LSTM) algorithm [19]. The introduction of a pre-processing phase, which involves cleaning the tweets using the Python Neat Text package, increased the accuracy of the sentiment analysis. This study used LSTM and the suggested pre-processing module to analyse sentiment in a corpus of 1,79,107 tweets about COVID-19. The findings showed that 96% of the time, the emotion expressed in these COVID-19 tweets could be accurately identified. However, the accuracy rate of the provided approach, which was based on ANN, was significantly lower at 76%. This work highlighted both the effectiveness of LSTM with preprocessing for SA and its value in extracting insights from large-scale textual

A. Ç. Korkmaz et al. (2023) designed to apply sentiment analysis to tweets in order to offer light on issues, opinions, and experiences pertaining to nursing education during the COVID-19 pandemic [20]. The results showed that nurses, school, health, education, and nursing were the most commonly used keywords. According to a sentiment analysis conducted during the pandemic, 84% of tweets were favourable, 12% were negative, and 4% were neutral. In order to empower more nurse professionals during tragedies like the COVID-19 pandemic, the results demonstrated the importance of valuing the work that nurses and nursing students conducted in responding to the pandemic and the necessity to make nursing education easier.

B. Fakieh et al. (2023) used the ABCML-SA model to describe the sentiments expressed in the tweets on COVID-19. Following initial data pre-processing, n-gram based feature extraction was performed to obtain the feature vectors [21]. The SVM model was used to identify and categorise the attitudes. Lastly, the SVM parameters for the ABC method were also changed. A series of simulations demonstrated the superiority of the suggested ABCML-SA model. The comparative analysis's findings demonstrated the ABCML-SA model's usefulness when compared to alternative approaches.

E. Hirata et al. (2023) examined Twitter data regarding logistics in Japan during the COVID-19 pandemic using natural language processing methods [22]. The BERT machine learning algorithm was used to measure the text's mood. During the analysis period, the results showed that logistics had a bright future. The study had four main ramifications: According to the research, (1) the word logistics was viewed favourably; (2) there was a tendency for interest in logistics to increase in western Japan in 2022; (3) social media data could be used to provide a more thorough and timely interpretation of transportation and logistics trends; and (4) the research showed that the logistics sector could benefit from the use of social media data.

W. Aljedaani et al. suggested a hybrid approach to sentiment analysis that combined lexicon-based techniques with deep learning models to increase sentiment accuracy [23]. In terms of the likelihood of incorrect annotations, the studies examined the impact of TextBlob on model classification accuracy in comparison to original data annotations. Additionally, TextBlob's performance was compared to Afinn's and VADER's. The findings demonstrated that when trained models employed sentiments assigned by TextBlob rather than sentiments found in the dataset, they performed better. Outperforming all other models, including previous studies, LMST-GRU achieved the highest accuracy of 0.97 and F1 scores of 0.96. The accuracy scores of the other tree classifier and the support vector classifier were 0.92 in BoW and TF-IDF, respectively.

S. H. Biradar et al. (2022) created big data technology that enabled sentiment analysis via real-time collection and processing of massive amounts of unstructured social media data [24]. Following preprocessing of the datasets, classification of the data according to certain domains, feature vectors according to the n-gram models, according to the feature vectors in the form of tf-idf vectors, synonym extraction, and sentiment analysis classification, the methodology yielded an algorithm based on sentiment analysis with the use of customer review classification. The developed tool made it easier for the user to compute, process, and comprehend relationships and interactions between individuals, topics, and ideas. Its accuracy was close to 80 percent, and it was 1.5 times faster than a traditional database on a Hadoop cluster.

S. Naeem et al. (2021) suggested employing sentiment analysis of Twitter comments, or tweets, to anticipate exchange rates using machine learning [25]. The information needed to create a dataset on the exchange rates between the US dollar (USD) and the Pakistani rupee (PKR) was obtained by collecting data from a forex website and a sample of tweets from the Pakistani business community that included financial-related terms. To better describe the data, it was visualised in 3-dimensional vector space using principal component analysis and linear discriminant analysis. The optimised dataset was subjected to five machine learning classifiers: the SVM, naive Bayes, bagging, RF, and basic logistic classifiers. With a forecast accuracy of 82.14%, the results showed that the basic logistic classifier was the most accurate at predicting the USD and PKR exchange rates.

III. Research Methodology

Different types of sentiments can be ascertained with the aid of the models for sentiment categorisation. The classification models consist of multiple processes, including feature extraction, classification, performance analysis, and data set pre-processing. Several approaches for effective sentiment classification were proposed in the preceding year. There are some restrictions on the current method that we must take into account when doing the research. Because the dataset is so large, the current approaches are unable to specify the relationship between each attribute and the target set. As explained below, sentiment analysis involves several steps:

A. Data Acquisition

This process is related to gathering data about different sentiments from social media while taking a number of aspects into account. This data is used to run the tests.

B. Data pre-processing

At this point, machine learning techniques are used to provide completeness and analyse the data. Additionally, this stage's main goal is to process the data in order to remove any redundant features from the dataset. As a result, the training system is enhanced to clean and de-noise data that is generated throughout the feature determination phase.

C. Feature selection

A subset works well for sentiment analysis because it has certain qualities. The current class of attributes is tackled by such attributes. The features are chosen using RF (Random

Forest). This algorithm uses an estimator with a value of 100. It creates a tree structure with a number of useful characteristics. It runs n regression trees and combines them into a single model to get predictions that are more accurate than it could with a single regression tree. RF creates a lot of decision trees during training, and the final forecast is the total of all the decision tree forecasts. Data scientists can use RF, often referred to as bagging in machine learning, to reduce the volatility of extremely volatile algorithms. Typically, decision trees employ these techniques. Bagging is repeated during feature X and output Y training, where trees are adjusted to the sampling that is chosen at random β times $(b = 1,2, \dots, \beta)$. A series of examples is produced by randomly selecting each tree in the training set. The sequence of events constitutes a given tree since they are random vectors. No two decision trees created from sequences will be same since no two sequences are alike. The K-th tree's forecast of an input X can be obtained using the equation.

$$h_k(X) = h(X, \emptyset_k), k \in \{1,2, \dots., K\} \tag{1}$$

The number of trees is K. To prevent feature correlations, each split of a tree chooses its properties at random. By identifying a gateway that lowers the variance in the sum of squared errors, the node S can be divided into two subsets, S_1 and S_2:

$$SSE = \left(\sum_{i \in S_i} \left(v_i - \frac{1}{|S_1|} \sum_{i \in S_1} v_i \right)^2 + \sum_{i: i \in S_2} \left(v_i - \frac{1}{|S_2|} \sum_{i \in S_2} v_i \right)^2 \right) \tag{2}$$

It is possible to anticipate the mean or median of the results of cases involving the same set of decision-making rules for each subtree. Lastly, the output of each tree can be averaged using Equation to produce the final forecast.

$$h(X) = \frac{1}{K} \sum_{i=1}^{K} h_k(X) \tag{3}$$

This formula is sufficiently adaptable to select the relevant characteristics for sentiment prediction.

D. Classification

The purpose of this procedure is to map the chosen attributes into the training system in order to categorise the supplied qualities. This allows for the successful prediction of coronary dysfunction. A sort of feeling is defined by each of the several classes. Since the learnt properties are fed into the algorithm, attitudes are classified using the LR (logistic regression) technique. The data was classified using LR, a machine learning (ML) technique. It is a prediction model that uses a linear combination of features to test the exponential criterion while using the standard logistic function. This method makes it simpler for users to comprehend the relationship between the dependent variable and a larger number of independent factors. This improved regression model may be applied when the dependent variable is nominal. This model's primary goal is to enable them to be informed by the data. In order to categorise an example into one of the two classes in our situation, a decision boundary, curve, or surface is created between the data. The association between a variety of independent factors and a specific type of dependent variable is explained using a probability model known as a logistic regression. The coefficients of the logistic function must be raised in order to identify the decision boundary. The cost of mitigating a cost is used to calculate the weight of each characteristic in the linear combination. In contrast to previous methods, it can also translate the output between 0 and 1 using an activation function, often Sigmoid. The likelihood of the output category is indicated by an output value between 0 and 1. A discrete value is generated as the output with the aid of this probability. The method can also be applied to multi-class classification. LR can be expressed mathematically as follows:

$$P = \frac{1}{1 + e^{-}(a + bx)} \tag{4}$$

where P (0) and P (1) are the probabilities in 0 and 1, X is an independent variable, a and b are parameters, and e is the base of natural logarithms. It also has three hyper-parameters that work with LR correctly. Additionally, using input data, this method can be used to continually estimate the chance of a particular outcome. Adding the final probability yields a stratification of all potential outcomes and chances of all. One of them is that a slight alteration in the input value has a detrimental lay effect on the final probability forecast

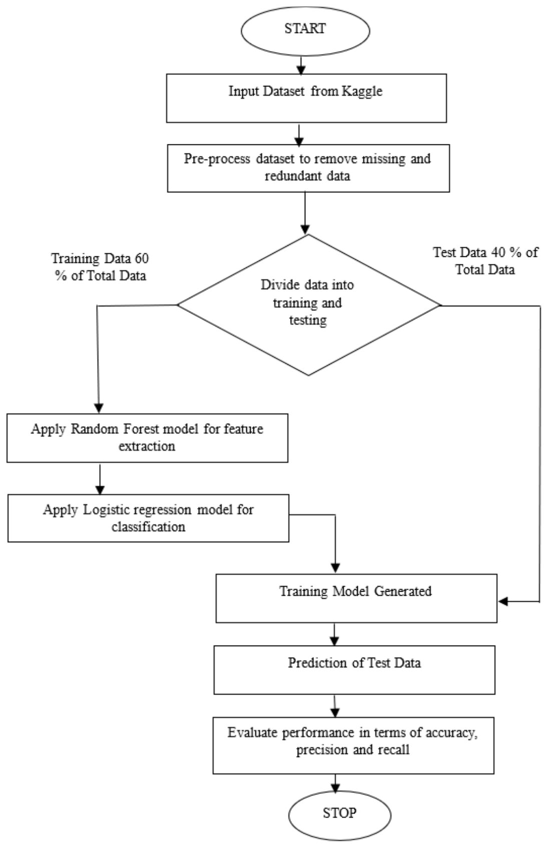

Fig. 1. Proposed Architecture

IV. RESULT & DISCUSSION

The study's suggested approach will be used to sentiment analysis of Twitter data. The proposed approach includes several phases, including pre-processing, feature extraction, and classification. Recall, accuracy, and precision are used to evaluate the performance of the proposed model.

A. Dataset Discription

One popular microblogging platform is Twitter. Millions of people utilize the personal accounts listed on this microblogging service. This is the page where consumers' personal information can be found. Consumers can connect with one another by following one another, and they can easily access other people's content. A survey found that 50 billion tweets were sent every day. Posts on Twitter have millions of opinions. Because Twitter is linked to a variety of online apps, it has received a lot of attention in the opinion mining field.

B. Performance Analysis Parameters

The performance Analysis parameters are described in this section in detail below: -

1) Accuracy: Accuracy is used to gauge how well the data field recovery and processing elements are executed. The fraction of results that will be successfully classified can be displayed using the following equation:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{5}$$

2) Precision: Precision is a performance statistic that calculates the proportion of correctly identified positives to all acknowledged positives. This can be seen in the following ways:

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

3) Recall: It is the ratio of connected instances recovered to total instances retrieved and is also known as recall. It looks like this:

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

C. Results

The suggested model is tested on real data using sentiment analysis. The existing models are compared with the suggested model.

TABLE I. DT'S OUTCOME

Class	Precision	Recall	F1-Score
0	0.79	0.71	0.75
1	0.66	0.74	0.79

TABLE II. NAÏVE BAYES'S OUTCOME

Class	Precision	Recall	F1-Score
0	0.87	0.90	0.89
1	0.86	0.82	0.84

TABLE III. MLP OUTCOME

Class	Precision	Recall	F1-Score
0	0.79	0.84	0.84
1	0.82	0.69	0.75

TABLE IV. ENSEMBLE MODEL

Class	Precision	Recall	F1-Score
0	0.86	0.84	0.84
1	0.84	0.85	0.82

TABLE V. PROPOSED MODEL

Class	Precision	Recall	F1-Score
0	0.94	0.93	0.94
1	0.95	0.95	0.95

TABLE VI. OVERALL RESULTS

Model	Accuracy	Precision	Recall	F1-Score
Decision Tree	75.41 Percent	75 Percent	75 Percent	75 Percent
Naïve Bayes	83.61 Percent	84 Percent	84 Percent	84 Percent
Multilayer Perceptron	83.61 Percent	85 Percent	84 Percent	84 Percent
Ensemble Model	85.25 Percent	86 Percent	85 Percent	86 Percent
Proposed Model	95.08 Percent	95 Percent	95 Percent	95 Percent

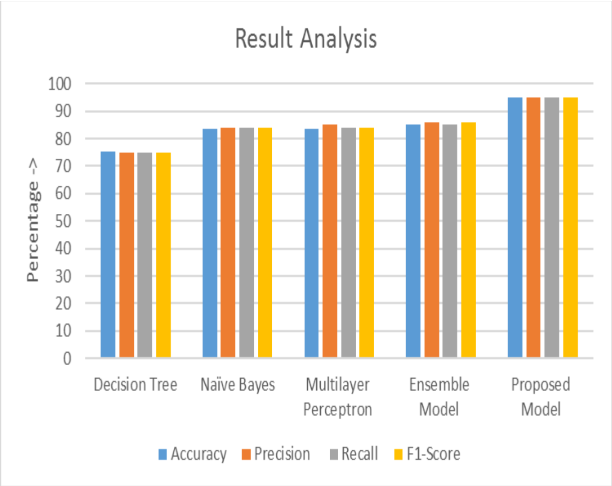

Fig. 2. Overall Analysis of the Results

As seen in figure 2, the general result of the proposed model contrasts with the existing models, which include decision trees, naive Bayes, multilayer perceptrons, and ensemble models. According to research, the suggested models should be able to achieve a maximum accuracy of 95% of sentiment analysis, or roughly 5% of what is now accomplished using emotional analysis models.

CONCLUSION

The significance of using ML approaches for efficient sentiment analysis is emphasised in this work. It illustrates how sophisticated analytical techniques can decrease redundancy, boost productivity, and enhance predicted accuracy by creating a methodical framework that combines data collection, preprocessing, feature selection, and classification. The most pertinent qualities were found through the successful feature selection process of Random Forest (RF), which decreased noise and improved model reliability. Furthermore, Logistic Regression (LR) offered a strong classification system that could mathematically differentiate between positive and negative feelings. This study shows how important sophisticated machine learning models are for thwarting sentiment analysis of Twitter data.

REFERENCES

[1] K. Yadav, A. Lamba, D. Gupta, A. Gupta, P. Karmakar and S. Saini, "Bilingual Sentiment Analysis for a Code-mixed Punjabi English Social Media Text," 2020 5th International Conference on Computing, Communication and Security (ICCCS), Patna, India, 2020, pp. 1-5

[2] E. Daniati, R. Firliana, A. S. Wardani and A. C. Zarkasi, "Evaluation Framework for Decision Making Based on Sentiment Analysis in Social Media," 2021 International Conference on Advanced Mechatronics, Intelligent Manufacture and Industrial Automation (ICAMIMIA), Surabaya, Indonesia, 2021, pp. 47-51

[3] S. Xiang, "Deep Learning Framework Study for Twitter Sentiment Analysis," 2021 2nd International Conference on Information Science and Education (ICISE-IE), Chongqing, China, 2021, pp. 517-520

[4] S. Singh, K. Kumar and B. Kumar, "Sentiment Analysis of Twitter Data Using TF-IDF and Machine Learning Techniques," 2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON), Faridabad, India, 2022, pp. 252-255

[5] A. Chowanda and Y. Muliono, "Indonesian Sentiment Analysis Model from Social Media by Stacking BERT and BI-LSTM," 2022 3rd International Conference on Artificial Intelligence and Data Sciences (AiDAS), IPOH, Malaysia, 2022, pp. 278-282

[6] Y. Chen, "TagNet: Toward Tag-Based Sentiment Analysis of Large Social Media Data," 2018 IEEE Pacific Visualization Symposium (PacificVis), Kobe, Japan, 2018, pp. 190-194

[7] H. -C. Soong, N. B. A. Jalil, R. Kumar Ayyasamy and R. Akbar, "The Essential of Sentiment Analysis and Opinion Mining in Social Media: Introduction and Survey of the Recent Approaches and Techniques," 2019 IEEE 9th Symposium on Computer Applications & Industrial Electronics (ISCAIE), Malaysia, 2019, pp. 272-277

[8] G. Mambelli, C. Prandi and S. Mirri, "What influences sentiment analysis on social networks: a case study," 2020 IEEE Symposium on Computers and Communications (ISCC), Rennes, France, 2020, pp. 1-6

[9] S. T. Kokab, S. Asghar and S. Naz, “Transformer-based deep learning models for the sentiment analysis of social media data”, Array, vol. 1, no. 2, pp. 17-26, 10 April 2022

[10] U. B. Mahadevaswamy and P. Swathi, “Sentiment Analysis using Bidirectional LSTM Network, Procedia Computer Science, vol. 21, no. 5, pp. 455-56, 31 January 2023

[11] D. Li, R. Rzepka and K. Araki, “HEMOS: A novel deep learning-based fine-grained humor detecting method for sentiment analysis of social media”, Information Processing & Management, vol. 57, no. 6, pp. 639-64, 20 June 2020

[12] A. Pimpalkar and J. Retna Raj R, “MBiLSTMGloVe: Embedding GloVe knowledge into the corpus using multi-layer BiLSTM deep learning model for social media sentiment analysis”, Expert Systems with Applications, vol. 15, no. 5, pp. 514-519, 13 May 2022

[13] Y. Wang, G. Huang, J. Li, H. Li, Y. Zhou and H. Jiang, "Refined Global Word Embeddings Based on Sentiment Concept for Sentiment Analysis," in IEEE Access, vol. 9, pp. 37075-37085, 2021

[14] S. Urolagin, J. Nayak and U. R. Acharya, "Gabor CNN Based Intelligent System for Visual Sentiment Analysis of Social Media Data on Cloud Environment," in IEEE Access, vol. 10, pp. 132455-132471, 2022

[15] A. Kukkar, R. Mohana, A. Sharma, A. Nayyar and M. A. Shah, "Improving Sentiment Analysis in Social Media by Handling Lengthened Words," in IEEE Access, vol. 11, pp. 9775-9788, 2023

[16] K. Zhang, Y. Zhu, W. Zhang, W. Zhang and Y. Zhu, "Transfer Correlation Between Textual Content to Images for Sentiment Analysis," in IEEE Access, vol. 8, pp. 35276-35289, 2020

[17] M. Bredice, Anna Vittoria Formisano, Sara Kullafi, Pasquale Palma, “Access to credit and fintech: A lexicon-based sentiment analysis application on Twitter data,” Research in International Business and Finance, Volume 77, Part A, 2025, 102875, ISSN 0275-5319, https://doi.org/10.1016/j.ribaf.2025.102875.

[18] A. Ba Alawi, Ferhat Bozkurt, “A hybrid machine learning model for sentiment analysis and satisfaction assessment with Turkish universities using Twitter data,” Decision Analytics Journal, Volume 11, 2024, 100473, ISSN 2772-6622, https://doi.org/10.1016/j.dajour.2024.100473.

[19] B. Valarmathi, N. Srinivasa Gupta, V. Karthick, T. Chellatamilan, K. Santhi, Dhanush Chalicheemala, “Sentiment Analysis of Covid-19 Twitter Data using Deep Learning Algorithm,” Procedia Computer Science, Volume 235, 2024, Pages 3397-3407, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2024.04.320.

[20] A. Ç. Korkmaz, “Public’s perception on nursing education during the COVID-19 pandemic: SENTIMENT analysis of Twitter data,” International Journal of Disaster Risk Reduction, Volume 99, 2023, 104127, ISSN 2212-4209, https://doi.org/10.1016/j.ijdrr.2023.104127.

[21] B. Fakieh, Abdullah S. AL-Malaise AL-Ghamdi, Farrukh Saleem, Mahmoud Ragab, “Optimal Machine Learning Driven Sentiment Analysis on COVID-19 Twitter Data, Computers,” Materials and Continua, Volume 75, Issue 1, 2023, Pages 81-97, ISSN 1546-2218, https://doi.org/10.32604/cmc.2023.033406.

[22] E. Hirata, Takuma Matsuda, “Examining logistics developments in post-pandemic Japan through sentiment analysis of Twitter data,” Asian Transport Studies, Volume 9, 2023, 100110, ISSN 2185-5560, https://doi.org/10.1016/j.eastsj.2023.100110.

[23] W. Aljedaani, Furqan Rustam, Mohamed Wiem Mkaouer, Abdullatif Ghallab, Vaibhav Rupapara, Patrick Bernard Washington, Ernesto Lee, Imran Ashraf, "Sentiment analysis on Twitter data integrating TextBlob and deep learning models: The case of US airline industry," Knowledge-Based Systems, Volume 255, 2022, 109780, ISSN 0950-7051, https://doi.org/10.1016/j.knosys.2022.109780.

[24] Shanta H. Biradar, J.V. Gorabal, Gaurav Gupta, "Machine learning tool for exploring sentiment analysis on twitter data," Materials Today: Proceedings, Volume 56, Part 4, 2022, Pages 1927-1934, ISSN 2214-7853, https://doi.org/10.1016/j.matpr.2021.11.199.

[25] S. Naeem, Wali Khan Mashwani, Aqib Ali, M. Irfan Uddin, Marwan Mahmoud, Farrukh Jamal, Christophe Chesneau, "Machine Learning-based USD/PKR Exchange Rate Forecasting Using Sentiment Analysis of Twitter Data," Computers, Materials and Continua, Volume 67, Issue 3, 2021, Pages 3451-3461, ISSN 1546-2218, https://doi.org/10.32604/cmc.2021.015872.