DOI: 10.52131/pjhss.2025.v13i4.3039

Pakistan Journal of Humanities and Social Sciences

Volume 13, Number 04, 2025, Pages 67-77
Journal Homepage:
https://journals.internationalrasd.org/index.php/pjhss

A Computational Sentiment Analysis for Emotion Classification in Occasion-Related English Language Tweets

Suhaira Talib[1], Bushra Shoukat[2]

[1] M.Phil. Scholar, Department of English Linguistics, Islamia University of Bahawalpur, Bahawalnagar Campus, Pakistan. Email: suhairatalib@gmail.com
[2] Assistant Professor, Department of English, Islamia University of Bahawalpur, Bahawalnagar Campus, Pakistan. Email: bushra.shoukat@iub.edu.pk

ARTICLE INFO

Article History:
Received: August 13, 2025
Revised: December 24, 2025
Accepted: December 25, 2025
Available Online: December 26, 2025

Keywords:
Sentiment Analysis
Natural Language Processing
Emotion Extraction
MNB
RF
LR

Funding:
This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ABSTRACT

In the age of digital communication, social media platforms like Twitter have become essential spaces for individuals to express emotions, particularly during significant national and religious events. This study investigates how well machine learning classifiers identify emotions in tweets that are posted on particular occasions. The research aims to determine the impact of sentiment classification accuracy and assess the performance of different classification models in identifying emotions in tweets shared during major events. The seven main emotions—joy, sadness, anger, fear, disgust, surprise, and neutral were represented in a dataset that was carefully gathered from twelve distinct events. To categorize emotions, three popular machine learning classifiers Multinomial Naïve Bayes (MNB), Random Forest (RF), and Logistic Regression (LR) were utilized, and their results were assessed using four important metrics: accuracy, precision, recall, and F1-score. The results demonstrated that Logistic Regression (LR) outperformed other classifiers, achieving the highest accuracy of 92%. Random Forest (RF) followed closely, with an accuracy of 91%, maintaining robust results in all emotional categories. Multinomial Naïve Bayes (MNB), with an accuracy of 89%, proved effective in cases where emotions had strong keyword associations. Logistic Regression emerged as the most effective classifier for sentiment analysis of occasional tweets, Random Forest provided a strong alternative, and Multinomial Naïve Bayes remained useful for keyword-driven sentiment detection.

Corresponding Author's Email: suhairatalib@gmail.com

1. Introduction

Every text or word used in speech has both lexical and contextual meanings because they provide context for the debate, emotions play a significant role In recent years, the extraction of emotions from text has been a prominent area of research. There are many different ways to convey emotion, such as through spoken words, written texts, body language, and facial expressions. A content-based classification challenge that combines ideas from machine learning and natural language processing is text emotion detection (Kumar & Geetha, 2024).

1.1. Social Media

Matisse, an online media platform established in Tokyo, is where the word "social media" (SM) first appeared in 1994 (Bercovici, 2010). Social media makes it possible for people to be or become social via exchanging news, photographs, material, and other kinds of information. There are hundreds of definitions of "social media," and new ones are being developed every day as the concepts evolve (Taprial & Kanwar, 2012). Merriam Webster states that in 2019,By employing social networks for digital communication, such as chatrooms, digital hub, and online websites or services can construct for online communication sharing views, opinions, facts, and other content. Definition of social media according to 2024 version of Web Dictionary are "Apps and

Webpages are used for social media interactions". Dollarhide's 2023 defines social networks as the technology that make it easier for people to share information and thoughts. With over 4.7 billion users, social media platforms including Facebook, Instagram, YouTube, and the X platform (previously Twitter) account for about 60% of the world's population. In early 2023, social networking sites ranked second at 94.6%, with round about 95% of users utilizing social media sites for messaging and chat. Social network sites were first used for socializing with close ones, but after that it quickly expanded to several purposes. After Facebook and X launched in 2004, usage of digital media blaze, with MySpace becoming the first network to achieve one million monthly active users. The Global Web Index shows that around 50% people who use internet get information or news from social networking sites (Dollarhide, 2023).

1.2. X (Formerly Known as Twitter)

Jack Dorsey, Christopher Isaac Stone, Noah E. Glass, Jeremy LaTrasse, and Evan Williams established the San Francisco-based company X on March 21, 2006. X served as a online platform that connected people to information, views, concepts, and news through its live streaming, comments, and chats. Elon Musk took over X, formerly known as Twitter, on October 27, 2022 (Ghazzawi, 2024). Notable and promising outcomes are obtained from machine learning-based emotion identification from text, as well as advancements in machine learning methods and technology (Chowanda et al., 2021). The ability to recognize human emotions in text is becoming increasingly important from an application perspective in computational linguistics (Kumar & Geetha, 2024).

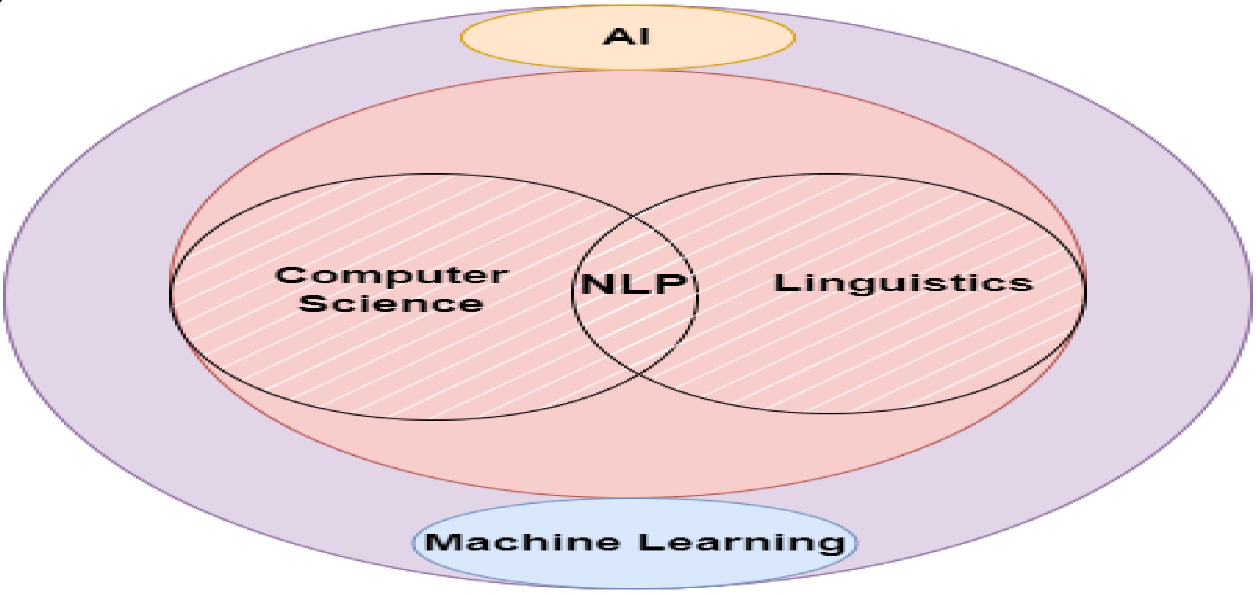
RQ1: What is the impact of the frequency of certain keywords or phrases in a tweet on the classification of its emotional tone?
RQ2: What are the accuracy, precision, recall, and F1-score of Emotions in Occasional Tweets using Multinomial Naive Bayes (MNB) classifier?
RQ3: What are the accuracy, precision, recall, and F1-score of Emotions in Occasional Tweets based on the Random Forest (RF) classifier?
RQ4: What are the accuracy, precision, recall, and F1-score of Emotions in Occasional Tweets by using the Logistic Regression (LR) classifier?
RQ5: Which Classifier gives the highest Classification report among MNB, RF, and LR Classifiers?

Statistical algorithms are used in machine learning approaches to analyze language data. The classifier for the supervised approach is trained and tested using an annotated emotion dataset. A study was carried out to use a bootstrapping framework alone to learn emotive hashtag lists (Qadir & Riloff, 2013). The scientific field of sentiment analysis examines and assesses the subjective content of textual data from social media discussions. In order to determine whether or not people are content with the subject being discussed, it mostly focusses on analysing the polarity of attitudes, ideas, and emotions. It shows projects in NLP and different fields of Linguistics such as computational Linguistics (Machová et al., 2020). Alotaibi's 2019 work identified emotions in textual content using a supervised learning-based Logistic Regression classifier. After the classifier was trained on the ISEAR dataset, its predictive power in emotion categorization was evaluated using an alternative testing dataset. The poor coverage of emotional cues, however, was a significant barrier that resulted in subpar performance. By incorporating a Logistic Regression classifier into the supervised learning methodology, his study gets over this restriction. The positive outcomes demonstrate that the recommended strategy outperforms comparable methods (Alotaibi, 2019). Poornima and Priya assess the effectiveness of different machine learning techniques for X data sentiment analysis. The suggested approach uses the frequency of a phrase to identify its emotional polarity(Ahmed, Azhar, & Mohammad, 2024; Mohammad, 2015; Mohammad & Ahmed, 2017). The effectiveness of the Multinomial Naive Bayes, Logistic Regression, and SVM methods for classifying sentences is assessed (Poornima & Priya, 2020). The results show that when logistic regression is combined with n-gram and Bigram models, it achieves 86% accuracy. This study uses the Random Forest approach to analyze sentiment on X data sources. This study looks at the algorithm's evaluation findings. Approximately 75% of the measures taken during this inquiry were accurate. The model produces favorable results (Bahrawi, 2019).

2. Theoretical Framework NLP

The area of NLP along computer science and computational linguistics transform written and spoken languages of humans into organized and extractable data. NLP combines linguistic, statistical, and artificial intelligence methods to determine a text's meaning or produce a response that is human-like (Fanni et al., 2023). Artificial intelligence and linguistics were combined to create NLP in the 1950s. Text information retrieval (IR), which effectively employs statistics to index and search vast volumes of text, is distinct from natural language processing (NLP). In 1963 the Backus Naur Form (BNF) notation was created after Chomsky's 1956 theoretical study of language grammar was used to estimate the problem's difficulty. Computer language syntax is commonly represented using the "context-free grammar" (CFG) defined by BNF. Derivation rules from a language's BNF definition provide syntactic validation for program code (Chomsky, 1956).

Figure 1: NLP



Machine translation, speech recognition, question answering, document summarisation, and speech synthesis are some of the uses of natural language processing (NLP). Sentiment analysis and emotion recognition are two fundamental components of natural language processing. Despite their occasional interchangeability, these two names are distinct. Sentiment analysis results can be favorable, negative, or neutral. Data points can be either positive or negative. A method for recognising particular emotions, such as joy, sorrow, or rage, is called emotion detection. Affective computing, emotion identification, emotion analysis, and emotion detection are all synonymous words (Munezero et al., 2014). Lexicons, which are collections of typical emotional phrases, were utilized in a study to identify emotions through a lexical method. Traditional techniques are no longer relevant because the advanced models for learning detection reliably identify sentiments from given data (D & Juliet, 2023). In NLP, word embedding is often employed in deep learning algorithms to identify semantic components and linguistic links between words (Ibrahiem et al., 2018).

3. Sentiment Analysis

Sentiment analysis uses Natural Language Processing (NLP) for sentiment or emotion extraction from several sources including text, speech, and social media posts. Sentiment extraction, sentiment classification, subjectivity classification, opinion summarization, and opinion spam detection are just a few of the tasks that fall under the umbrella of sentiment analysis. It seeks to understand how people feel and think in a range of situations, such as different topics, incidents, developments, and resources. It appears difficult for projects requiring text analyses, computational linguistics, and NLP (Machová et al., 2023).

3.1. Sentiment Analysis Approaches

Sentiment analysis on linguistic data can be done in many different ways. Most sentiment analysis research uses lexicon-based analytic techniques or machine learning. Machine learning and lexicon-based methods are the two main methods for sentiment analysis (Olsson, 2009). This study aligns with machine learning approach.

3.2. Machine Learning Approaches

ML classification of text used algorithms that are based on machine learning method. By identifying linguistic input and utilizing machine learning algorithms to show it in vector form, ML approaches manage the processing of data. Sentiment analysis literature frequently uses ML techniques like Random Forest, Naïve Bayes, and Logistic Regression to analyze sentence terms as vectors. In machine learning methods we trained models to extract or analyze text on basis of sentiments. Because the model is trained with labelled source data, supervised learning frequently performs on unsupervised and semi- supervised learning methods (Vicari & Gaspari, 2021). Techniques for machine learning fall into two categories.

Unsupervised learning: It requires clustering because it does not have a category and does not offer precise targets.

Supervised learning is a useful method for classifying problems: The model gets the labels during processing because it is built on a labelled dataset. Data prediction accuracy is increased through classifier training. Supervised learning is the main technique of machine learning for sentiment analyses (D & Juliet, 2023).

3.3. MLClassifiers

In this study the ML algorithms that helped with text categorization are following.

3.4. Multinomial Naive Bayes (MNB)

In NLP the most popular classifier is Multinomial Naive Bayes. This methodology works well for classifying texts. Multinomial Approach a variable effect on a class is assumed to be independent of other variables by Bayes classifiers. This is the meaning of "class conditional independence." It is meant to make the computation simpler and is regarded as "Naive" (Sahayak, Shete, & Pathan, 2015). Sentiment tags are equally important to the categorization process as other dataset tokens. Other characteristics will no longer be considered when using this classifier in machine learning to categorize the sentiment labelled. Multinomial Naive Bayes was used to classify "Tweet Sentiment" based on a single attribute (Patel, 2017).

3.5. Logistic Regression (LR)

Logistic regression (LR), a machine learning technique, classifies emotion from text using training data (Dhanalakshmi et al., 2023). LR is the regression method to use when the dependent variable is binary. Like any regression analysis, it is a statistical method. It explains the text and shows the relationship between different independent nominal, ordinal, interval, or ratio-level variables and same with dependent binary variables (Golam Mostafa & Junayed, 2021).

3.6. Random Forest (RF)

A supervised machine learning technique based on ensemble learning is called Random Forest (RF). A more potent prediction model can be produced using ensemble learning, which combines multiple repetitions of the same algorithm or various algorithm types (Bahrawi, 2019). In 2001, Adèle Cutler and Leo Breiman offically proposed RF. It is a kind of method for automatic learning (Breiman, 2001).

3.7. Used Software

The model was programmed and the code uploaded using the Anaconda software. Anaconda is an open-source Python distribution created especially to support scientific computing, machine learning, and data analysis. Anaconda is an integrated package management that makes it simple to install and maintain necessary libraries and dependencies. Our project employs Jupyter Notebook with Anaconda for sentiment analysis to extract emotions from tweets.

4. Methodology

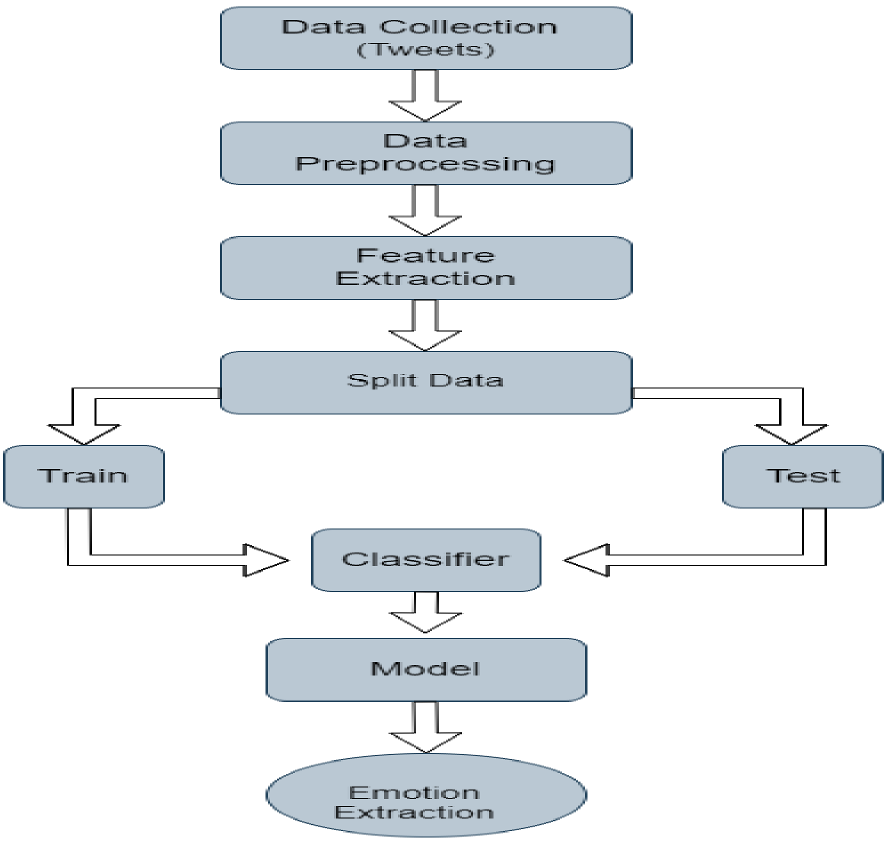
The purpose of this study, to analyze the sentiment in occasional tweets and use NLP to extract emotions. The foundation of Computational technique to Extract emotions using NLP fall in quantitative computational method that combines descriptive and exploratory research. To ascertain the type of irregular tweets and their linguistic features, this study starts in an experimental way in which text dataset gathered from X is examined. The dataset is cleaned using preprocessing methods such text cleaning, stop word removal, lemmatization, and NLP feature extraction to eliminate uninformative data, including hashtags, mentions, punctuation, and stop words. We created pipelines for computer models after preparing the data and dividing it into training and testing stages. The research focusses on creating and refining different deep learning and machine learning models to categorize particular emotions. The final result showed how well RF, MNB, and LR models performed analysis of sentiments inoccasional tweets. The use of Natural Language Processing (NLP) components is the main focus of this study's research technique. The fundamental methodology preprocesses and analyses tweets and brief textual material gathered from certain events, national holidays, and cultural festivals in Pakistan using Sentiment Analysis (SA), a natural language processing technique. Text cleaning, stop word removal, and lemmatization are among the preprocessing techniques used in the strategy to prepare tweet data for analysis. Words that are cleaned and translated into numerical features are extracted in order to retrieve the meaning of words in tweets through Count Vectorizer among other procedures. After performing the extraction of features, the classification of the emotional content of tweets is carried out with the help of such ML techniques like MNB, LR, and RF. These models have been trained to identify and classify the various emotions such as sadness, anger, disgust, fear, surprise and joy. The primary goal of this study is computationally extract emotions from tweets using an NLP driven sentiment analysis methods, ML intended for occasional tweets from online media platform.

4.1. Preprocessing of Data

It is essential to remind that the numerous combinations, unique characters, slang, and language used in SMS are not even covered by dictionaries.

- To create consistency, start by making the entire text lowercase, eliminating any punctuation, and eliminating stop words like prepositions.
- To understand anything significant, we must reduce the text word into its most fundamental form. In this way, all words in the text are reduced to their most basic form, even those in the past tense and plural. We refer to it as lemmatization. Another piece of code that I have added is the reversal of repetition of letters in a word since there are not many words with more than two letters in a row. We must pre-process the dataset after it has been collected. The preprocessed material was then split into two pieces for testing and training. Next, we used an ML classifier for each NLP feature extraction model that we used independently on the training dataset. After finishing this part, we used the data we had stored for testing to test our model. By then, it will be evident which model has the best f1-score, accuracy, precision, and recall. Together with the ML classifier, the optimal feature extraction model may then be found.

Figure 2: Hierarchical Structure of Research Philosophy



4.2. Data and Data Collection

On the social networking and microblogging platform X, users can post real-time communications called tweets. 140 characters make up a tweet. Because of the nature of this microblogging service, users may utilize abbreviations, misspellings, emoticons, and other characters with specific meanings. For this investigation, erratic tweet data was manually collected using the X website. Data was collected from January 2023 to May 2024, when X occasionally published tweets. We collected 1530 tweets regarding several national and religious festivals in Pakistan based on seven different human emotions: joy, grief, wrath, fear, surprise, disgust, and neutrality. Our dataset consists of four columns: the tweet ID, the emotion it reflects, the text content of the tweet, and the tweet type. We use tweets from both famous people and everyday people in our collection.

Figure 3: Dataset of Tweets

	Emotion	Text	Tweet ID	Type
0	Joy	Eid Mubarak to all	Abrar Ul Haq	religious
1	Joy	Late Eid Mubarak to all twitter friends and fo...	M Haleem Ishaq	religious
2	Joy	I spent a terrific weekend in Peel Region, vis...	Yasir Naqvi	religious
3	Joy	From the Capital of Pakistan Islamabad, we sta...	Hussain	religious
4	Joy	On this special day, may Allah shower his bles...	Khaled Shaik	religious
...	...	...	...	...
1526	Disgust	The stark contrast between words and actions o...	Adeelah Khan	National
1527	Disgust	The repetitive speeches on Kashmir Solidarity ...	Nadir Ahmed	National
1528	Disgust	The commercialized aspects of Kashmir Solidari...	Hira Javed	National
1529	Disgust	The disconnection between solidarity declarati...	Danish Farhan	National
1530	Disgust	The use of Kashmir Solidarity Day for politica...	Sidra Rehman	National

1531 rows × 4 columns

4.3. Preprocessing the Data

Some basic functions for language processing activities are needed in order to run our model using Python as a computer language. Advanced capabilities for processing linguistic data was made possible by a number of language processing approaches. Pre- processing is necessary to convert unstructured text into a format that NLP algorithms can efficiently handle due to the complexity of human language. There are various procedures in this preparation phase: feature extraction, stemming and lemmatization, stop word removal, and text cleaning and normalization (Kobayashi, Inui, & Matsumoto, 2007).

5. Results and Discussion

The Twitter app provided an Excel file with the data set for the sentiment analysis of occasional tweets. From January 2023 to May 2024, 1,531 English-language tweets representing Pakistan's culture, history, and sense of pride were collected from a range of significant occasions and events.

Table 1: Tweets Division

Sr.	Name of Occasion	Number of Tweets
1.	Eid-ul-Fitr	225
2.	Eid-ul-Adha	80
3.	Ramzan	100
4.	Quaid Day	185
5.	Iqbal Day	122
6.	Labour Day	188
7.	Defence Day	80
8.	Pakistan Resolution Day	90
9.	Independence Day	147
10.	Kashmir Solidarity Day	315

5.1. Build Model

Data cleaning and preprocessing were followed by the model creation stage. The dataset was split into two subsets at the beginning of this phase: 30% for testing and 70% for training. The models were able to find patterns and links in the data by developing and improving them on the training dataset. After the model was trained, its predicted accuracy and generalizability to new data were assessed using the testing dataset. To find the best model, the split datasets were subjected to three popular classification algorithms: Multinomial Naive Bayes, Random Forest, and Logistic Regression. Each classifier's capacity to correctly predict outcomes was assessed, and the classifiers' performances were compared using important assessment metrics like accuracy, precision, recall, and F1 score.

Confusion matrices: Confusion metrics are the most widely used and traditional assessment metrics. A confusion matrix is a table that shows prediction data in the form of True Positives, False Positives, True Negatives, and False Negatives. The results are shown below. Confusion matrix is used to show the actual classification of the values of the model on a test data set. The confusion matrix is a crucial matrix for sentiment categorization prediction (Giachanou & Crestani, 2017).

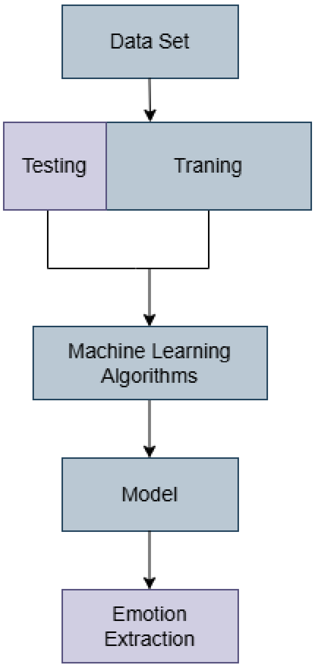
Accuracy: Accuracy is the percentage of all positive predictions made by prediction methods, including the negative predictions made by prediction methods, which are actually true. The accuracy of a model is determined by then dividing the total number of predictions that the model has made by the number of correct classifications that the model has made (Duhan & Arunachalam, 2024).

Recall: The advantages and disadvantages of each algorithm were exposed through this recurrent training and testing process. Through performance evaluation, the study aimed to discover the model that would be most appropriate for both managing the informal and diverse character of the dataset and effectively identifying subtle emotions (Afreen, Amir, & Farooq, 2024).

Precision: The performance of an AI model is evaluated by the use of a metric that measures the accuracy of one of the positive predictions made by the model. Accuracy, on the other hand, is obtained by dividing the true positives by the number of positive forecasts (Afreen & Bajwa, 2021).

F1-Score: The same level of importance is attached to the F-measure calculation, which is the harmonic mean of the recall and precision. Therefore, model performance can be characterized, and models may be compared using a single score that evaluates a model based on precision and recall. When the distribution of classes is similar, accuracy can be utilized (Afreen et al., 2023).

Figure 4: Build Model

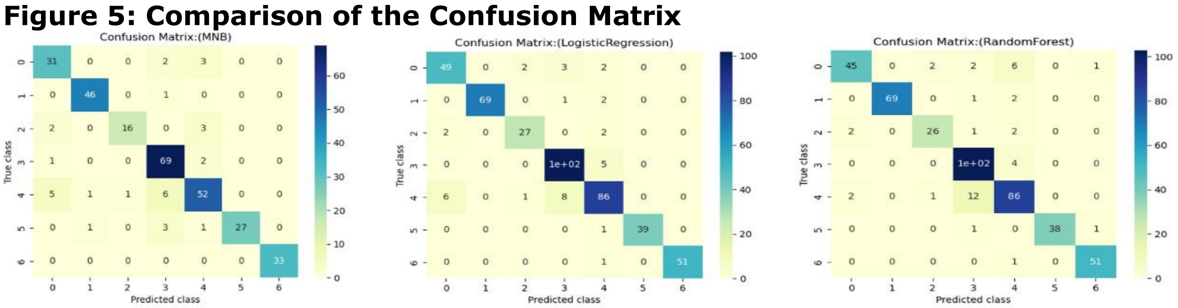


5.2. Comparison of Models

The following diagrams compare all the models that were applied in this study.

5.3. Confusion Matrix Comparison

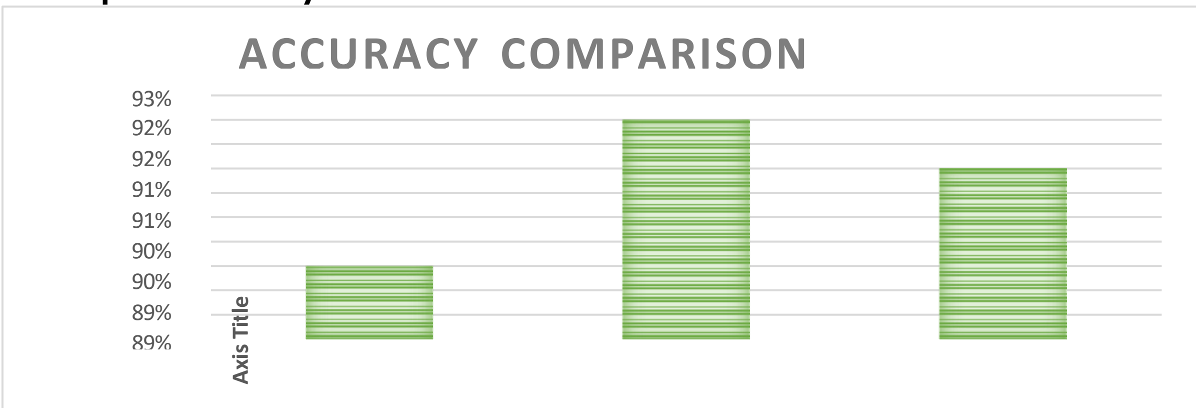
Figure 5: Comparison of the Confusion Matrix



MNB Logistic Regression Random Forest

5.4. Comparison of Accuracy

Figure 6: Comparative Analysis of Different Models

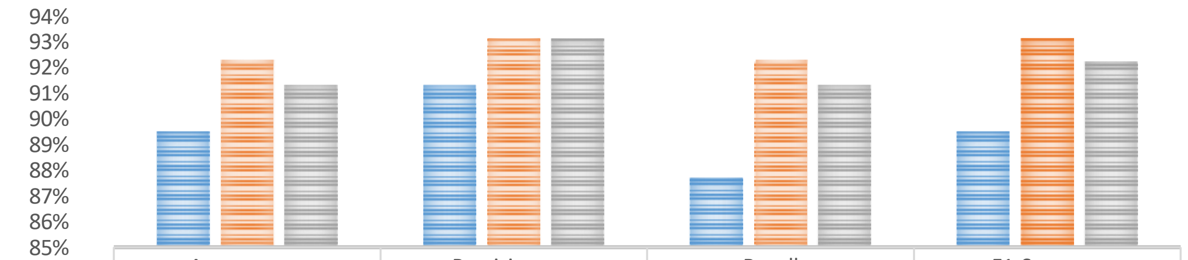


	MNB	LR	RF
Accuracy	89%	92%	91%

The results showed that the Logistic Regression Classifier yielded the best results. Logistic Regression performed better than the other models in terms of accuracy. The most accurate model was logistic regression.

5.5. Classification Report of All Used Models Comparison

Figure 7: Comparison of the Classification Report of Three Models



	Accuracy	Precision	Recall	F1-Score
	89%	91%	87%	89%
MNB	92%	93%	92%	93%
LR RF	91%	93%	91%	92%

The above diagram provides a detailed comparison of every model. The Logistic Regression Classifier had the best accuracy in Figure 7.

6. Conclusion and Findings

This study looked at how well Multinomial Naïve Bayes (MNB), Random Forest (RF), and Logistic Regression (LR) identified moods in sporadic tweets. Each classifier contributed uniquely to the sentiment classification process, with varying levels of accuracy and performance among seven emotion categories. With an overall accuracy of 92%, Logistic Regression (LR) had the highest performance among them, properly identifying 92 out of 100 cases. Compared to Random Forest (RF), which had an accuracy of 91%, and Multinomial Naïve Bayes (MNB), which had an accuracy of 89%, this performance was marginally superior. By highlighting the variations in each model's capacity to recognize and categorize particular emotional tones in tweets, the categorization reports further highlighted the advantages of each model.

Logistic Regression (LR) delivers high precision, recall, and F1-scores among all seven emotion categories. It performed exceptionally well in detecting emotions such as disgust (F1-score: 100%), surprise (F1-score: 99%), and neutral (F1-score: 100%), proving its ability to accurately classify emotions with high reliability. Because of its balanced character, LR is an excellent option for sentiment classification in tweets with contextual variations because it can identify both simple and complicated emotional expressions. Additionally, LR successfully managed word frequency fluctuations and feature selection, resulting in a stable and reliable classification across several categories. In terms of classification performance, Random Forest (RF) came in second, showing robust and consistent outcomes for each of the seven emotions. This classifier really benefited from its ensemble learning strategy, which reduces overfitting and increases classification accuracy by combining several decision trees. RF demonstrated particularly strong results in disgust (F1-score: 98%) and neutral (F1-score: 97%), showcasing its ability to detect emotions with high precision. The classifier's solid performance made it a dependable choice for emotion classification tasks because of its capacity to process massive volumes of data and identify significant patterns. It performed effectively in situations where emotions were complex and context-dependent because of its stability and capacity to adapt to various sentiment expressions.

When emotions had significant keyword correlations, Multinomial Naïve Bayes (MNB) continued to be an efficient classifier. MNB is well-suited for identifying emotions that are clearly portrayed in text because it mainly focusses on the frequency of particular words. Its classification performance was notable for emotions that relied on distinct word patterns, even though it did not surpass LR and RF in total accuracy. Because of this, MNB is especially helpful for examining tweets that have a high correlation between specific phrases and emotions. It was less successful in more complicated classification cases, though, because it had trouble managing sentiment variations that called for a richer contextual knowledge. Because it provides the finest combination of accuracy, precision, recall, and F1- score, Logistic Regression (LR) has been found to be the most successful classifier overall. This makes it the most dependable option for sentiment classification in sporadic tweets. However, Random Forest (RF) also showed competitive performance, with good classification accuracy and stability made possible by its ensemble-based methodology. For text-driven sentiment classification, where keyword frequency was important, Multinomial Naïve Bayes (MNB) continued to be a useful classifier. Every classifier made a distinct contribution to the sentiment analysis process, showcasing their distinctive abilities to categorize emotions in sporadic tweets. The results indicate that, although Logistic Regression is the best model overall, Random Forest is a good substitute, and MNB is still helpful for sentiment recognition based on keywords. The study explores tweet sentiment classification using traditional ML models and suggests deep learning methods like BERT to better capture sarcasm and emotion. It recommends addressing class imbalance, bias, and expanding to multilingual data for improved real world applications.

References

Afreen, H., Amir, A., & Farooq, U. (2024). An iot-assisted patient monitoring and alert system. *Journal of Computing & Biomedical Informatics*.

Afreen, H., & Bajwa, I. S. (2021). An IoT-Based Real-Time Intelligent Monitoring and Notification System of Cold Storage. *IEEE Access*, *9*, 38236-38253. https://doi.org/10.1109/ACCESS.2021.3056672

Afreen, H., Kashif, M., Shaheen, Q., Alfaifi, Y. H., & Ayaz, M. (2023). IoT-Based Smart Surveillance System for High-Security Areas. *Applied Sciences*, *13*(15), 8936. https://doi.org/10.3390/app13158936

Ahmed, D. M., Azhar, Z., & Mohammad, A. J. (2024). Integrative Impact of Corporate Governance and International Standards for Accounting (IAS, IFRS) in Reducing Information Asymmetry. *Polytechnic Journal of Humanities and Social Sciences*, *5*(1), 567-582.

Alotaibi, F. M. (2019). Classifying Text-Based Emotions Using Logistic Regression. *VAWKUM Transactions on Computer Sciences*, 31-37. https://doi.org/10.21015/vtcs.v16i2.551

Bahrawi, N. (2019). Sentiment Analysis Using Random Forest Algorithm-Online Social Media Based. *Journal of Information Technology and Its Utilization*, *2*(2), 29. https://doi.org/10.30818/jitu.2.2.2695

Bercovici, J. (2010). Who coined "social media"? Web pioneers compete for credit. *Forbes. Disponível*.

Chomsky, N. (1956). Three models for the description of language. *IEEE Transactions on Information Theory*, *2*(3), 113-124. https://doi.org/10.1109/TIT.1956.1056813

Chowanda, A., Sutoyo, R., Meiliana, & Tanachutiwat, S. (2021). Exploring Text-based Emotions Recognition Machine Learning Techniques on Social Media Conversation. *Procedia Computer Science*, *179*, 821-828. https://doi.org/10.1016/j.procs.2021.01.099

D, D., & Juliet, S. (2023, 2023-8-10). Sentimental Analysis Based on User Emotions Using Machine Learning. 2023 International Conference on Circuit Power and Computing Technologies (ICCPCT),

Dhanalakshmi, P., Kumar, G. A., Satwik, B. S., Sreeranga, K., Sai, A. T., & Jashwanth, G. (2023). Sentiment analysis using VADER and logistic regression techniques. 2023 international conference on intelligent systems for communication, IoT and security (ICISCoIS),

Dollarhide, M. (2023). Social media: Definition, importance, top websites & apps. *Diunduh di https://www. investopedia. com/terms/s/so cial-media. asp*.

Duhan, A., & Arunachalam, N. (2024). Book recommendation system using machine learning. AIP Conference Proceedings,

Fanni, S. C., Febi, M., Aghakhanyan, G., & Neri, E. (2023). Natural Language Processing. In M. E. Klontzas, S. C. Fanni, & E. Neri (Eds.), *Introduction to Artificial Intelligence* (pp. 87-99). Springer International Publishing.

Ghazzawi, I. (2024). At the helm of Twitter: the leadership style of Elon Musk. *Journal of Case Research and Inquiry*, *9*, 78-107.

Giachanou, A., & Crestani, F. (2017). Like It or Not: A Survey of Twitter Sentiment Analysis Methods. *ACM Computing Surveys*, *49*(2), 1-41. https://doi.org/10.1145/2938640

Golam Mostafa, I. A., & Junayed, M. S. (2021). Investigation of different machine learning algorithms to determine human sentiment using Twitter data. *International Journal of Information Technology and Computer Science (IJITCS)*, *13*(2), 38-48. https://doi.org/10.5815/ijitcs.2021.02.04

Ibrahiem, S., Bahnasy, K., Morsey, M., & Aref, M. (2018). FEATURE EXTRACTION ENCHANCEMENT IN USERS'ATTITUDE DETECTION. *International Journal of Intelligent Computing and Information Sciences*, *18*(2), 1-13.

Kobayashi, N., Inui, K., & Matsumoto, Y. (2007). Extracting aspect-evaluation and aspect-of relations in opinion mining. Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL),

Kumar, S., & Geetha, A. (2024). Emotion detection from text using natural language processing and neural networks. *Int. J. Intelligent Systems and Applications in Engineering*, *12*(14), 609-615.

Machová, K., Mikula, M., Gao, X., & Mach, M. (2020). Lexicon-based Sentiment Analysis Using the Particle Swarm Optimization. *Electronics*, *9*(8), 1317. https://doi.org/10.3390/electronics9081317

Machová, K., Szabóova, M., Paralič, J., & Mičko, J. (2023). Detection of emotion by text analysis using machine learning. *Frontiers in Psychology*, *14*, 1190326. https://doi.org/10.3389/fpsyg.2023.1190326

Mohammad, A. J. (2015). *The effect of audit committee and external auditor characteristics on financial reporting quality* Master Thesis, Universiti Utara Malaysia].

Mohammad, A. J., & Ahmed, D. M. (2017). The impact of audit committee and external auditor characteristics on financial reporting quality among Malaysian firms. *Research Journal of Finance and Accounting*, *8*(13), 9-16.

Munezero, M., Montero, C. S., Sutinen, E., & Pajunen, J. (2014). Are They Different? Affect, Feeling, Emotion, Sentiment, and Opinion Detection in Text. *IEEE Transactions on Affective Computing*, *5*(2), 101-111. https://doi.org/10.1109/TAFFC.2014.2317187

Olsson, F. (2009). A literature survey of active machine learning in the context of natural language processing.

Patel, R. (2017). *Sentiment analysis on Twitter data using machine learning*

Poornima, A., & Priya, K. S. (2020, 3/2020). A Comparative Sentiment Analysis Of Sentence Embedding Using Machine Learning Techniques. 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS),

Qadir, A., & Riloff, E. (2013). Bootstrapped learning of emotion hashtags# hashtags4you. Proceedings of the 4th workshop on computational approaches to subjectivity, sentiment and social media analysis,

Sahayak, V., Shete, V., & Pathan, A. (2015). Sentiment analysis on twitter data. *International Journal of Innovative Research in Advanced Engineering (IJIRAE)*, *2*(1), 178-183.

Taprial, V., & Kanwar, P. (2012). *Understanding social media*. Bookboon.

Vicari, M., & Gaspari, M. (2021). Analysis of news sentiments using natural language processing and deep learning. *AI & SOCIETY*, *36*(3), 931-937. https://doi.org/10.1007/s00146-020-01111-x