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Sentimental Analysis on Twitter: Insights from Supervised Learning

Ms. Purvi Rawal[1] , Ms. Anisha Asirvatham[2],

[1] **Student, Department of MSc.IT, Nagindas Khandwala College, Mumbai, Maharashtra, India**

[2]**Assistant Professor, Department of Computer and Information Science, Nagindas KhandwalaCollege, Mumbai, Maharashtra, India**

Abstract: Sentimental analysis is use for analyzing the text so that it can determine the emotions what is in the message which can be positive, negative, or neutral. Social media platforms such as twitter, Instagram, Facebook, etc. where public opinions have been expressed a lot. Other sentimental analysis algorithms include the rules-based and hybrid approach for data processing. Sentiment algorithms are also analysed accordingly with in forms of text like sentences, It also contains relevant interpretations through the information that was provided. In this study, a baseline model was first established, achieving an accuracy to serve as a comparison point for more sophisticated models. The Logistic Regression model outperformed the baseline significantly, demonstrating its effectiveness in accurately classifying sentiments. The Decision Tree Classification model, while an improvement over the baseline was less accurate than Logistic Regression, suggesting potential issues with overfitting and data dependency. The Random Forest Classification model provided a robust alternative, matching the performance of Logistic Regression and benefiting from the ensemble approach to handle diverse patterns in the sentiment data.

Keywords: Sentimental analysis, Machine learning, supervised learning, twitter

INTRODUCTION:

Twitter which covers around millions of users to share their thoughts, opinions and reactions towards different real time communication channel evolving around real time and it also includes shortness of the length and real time features of the Twitter through extraction useful data through real time communication. Sentiment analysis of Twitter data includes extracting, classifying, and interpreting sentiments expressed in tweets, which were posted through this platform by many people in a bid to understand the pulse of the public mood, consumer behaviour, and social trends. Sentiment analysis, otherwise called opinion mining, is a sub-discipline of NLP for sentiment identification using computers and opinion classification expressed in textual data. Having invented digital ways of communication, huge amounts of text data are created daily via social media, online reviews, blogs, and forums. This information explosion of unstructured data has created a growing need for tools and techniques to analyse and interpret sentiments behind these textual inputs. Sentiment analysis on Twitter is problematic, however, since this site recognizes special features. Indeed, such a constraint can result in concise and sometimes ambiguous sentiment expressions, hence a problem when trying to accurately determine the emotional tone expressed. While these add useful context, they require special handling to be integrated effectively into sentiment models. Therefore, they can virtually respond within seconds to customer feedback or uptake in emerging trends.

PROPOSED SYSTEM:

The proposed system for sentiment analysis of Twitter data is designed to classify tweets into positive, negative, and neutral categories using three different machine learning algorithms: Logistic Regression, Decision Tree Classification, and Random Forest Classification. The system begins with a baseline model, which serves as a fundamental reference, providing a benchmark against which the performance of more sophisticated models can be compared. Logistic Regression significantly outperforms the baseline. The Decision Tree Classification model, while also improving upon the baseline. The Random Forest Classification model enhances performance by using an ensemble of decision trees. Negative tweets often include terms such as indicating dissatisfaction and frustration. Neutral tweets, which focus on factual reporting, commonly feature words. Overall, the proposed system effectively combines model performance and word frequency analysis to provide a comprehensive understanding of sentiment distribution in Twitter data, with Logistic Regression and Random Forest emerging as the most effective classifiers for this task.

LITERATURE REVIEW

Birajli. M, et al (2021) The authors had survey by using traditional approaches for sentiment analysis based on a lexicon or machine learning techniques and highlight their respective strengths and limitations. They also explain more recent state-of-the- art methods that have been developed in the last two decades, especially deep learning approaches that involve convolutional neural networks, recurrent neural networks, and attention mechanisms. It also discusses trends in areas like multimodal data integration, such as text, image.

Chan. JYL, et al (2023) The research was featured in Artificial Intelligence Review, and it considered ways through which transfer learning can enhance sentiment analysis by considering a range of models pre-trained prior on vast datasets and testing them after fine-tuning for tasks that were more specific in nature. The review ranges from some transfer learning frameworks, which include BERT, GPT, and XL Net, showing improvements in accuracy and efficiency in sentiment classification.

Cui. J, et al (2023) The article had given comprehensive review of the progress made in methodologies of sentiment analysis and its important research themes, all the way from the early lexicon-based and machine learning methods to advanced deep learning models such as LSTMs, CNNs, and transformer-based architectures. The authors trace the evolution of topics in sentiment analysis, which includes tracks where the community is shifting towards real-time processing, The study has also identified ongoing challenges like handling sarcasm, context-awareness, and domain adaptation.

Dang. NC, et al (2020) The authors had considered deep learning models for the task of sentiment classification: Convolutional Neural Networks, Recurrent Neural Networks, Long Short-Term Memory networks, and hybrid models. Experiments are conducted using benchmark datasets, and performance comparisons among these models have been drawn in terms of accuracy, precision, recall, and F1-score.

Results indicate that LSTM and hybrid models outperform the traditionally used methods in most cases, much as expected.

Liu. H, et al (2020) The author had Surveyed that the state-of-the-art deep learning methods proposed for aspect-based sentiment analysis, among them being Convolutional Neural Networks and Recurrent Neural Networks. They are strong in extracting and analyzing aspects with sentiments at an aspect level and the attention mechanism. Some of the challenges related to handling implicit aspects are underlined, and a large amount of labeled data is required.

Ligthart. A, et al (2020) The paper had provided a review of the systematic reviews in the domain of sentiment analysis. The authors conducted a tertiary study to consolidate these findings of many secondary studies to perceive the trends, methodologies employed, and gaps in the existing research. The sentiment review article classifies the techniques under headings such as lexicon-based and machine learning and deep learning methods, along with their respective strengths and weaknesses. Key challenges highlighted in this area include handling sarcasm, context variability, and multilingual data.

Mehta. P, and Pandya. S, (2020) It provides an in-depth review of various techniques used in sentiment analysis. The evolution of the methodologies from the traditional approaches of machine learning to the modern deep-learning models is very well elaborated in that review. It discusses the practical application of sentiment analysis in various domains like marketing, finance, and social media monitoring. Further, it handles issues related to sentiment analysis, such as language ambiguities and the need for huge annotated datasets.

Nandwani. P, and Verma. R, (2021) In this paper the author did sentiment analysis with emotion detection from text, present an in- depth review in the context of Social Network Analysis and Mining, 2021. Various techniques for the same, ranging from classical machine learning to lexicon-based methods and modern deep learning approaches, are discussed. Context is applied to explain accurately sentiments and emotions. It also shows the practical application in areas such as monitoring social media, analysis of customer feedback.

Taherdoost. H, and Madanchian. M, (2023) This article, published in considers new developments in AI-driven techniques for sentiment analysis applied to gaining competitive intelligence. The different methodologies highlighted by the authors are machine learning and deep learning, and their effectiveness in extracting consumer sentiment and market trends were mentioned. Presenting the challenges related to data quality and algorithmic bias, the authors propose some solutions toward accuracy andreliability.

Tan. KL, et al (2023), The author had given a view of current popular deep learning models with an application to sentiment analysis, which are described, evaluated, and further compared. In summary, the results indicate that LSTM and hybrid models were generally better than other methods in this area because of their ability to model temporal dependencies and complex patterns of text. This paper reviews strengths and weaknesses of each model, underlining the paramount role of both an appropriate model architecture and hyperparameter tuning toward optimal results.

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Rodriguez. M, et Al (2023) The paper had given a description of different techniques used in conducting sentiment analysis on social media data. Because of the informal and very diverse language on social media, it reviews methodologies ranging from lexicon-based approaches to machine learning models and advanced deep learning techniques, describing the effectiveness and limitations for processing such text. In this sense, the authors highlight preprocessing steps and feature extraction as key toenhancing the performance of the model.

Wankhede. M, et al (2022) The survey article by author had contained all the relevant details related to SA methods, applications, and challenges in the field. The authors group SA methods into three broad categories: lexicon-based approaches, mainly dependent on pre-defined dictionaries of sentiment-bearing terms but failing to preserve most often contexts; machine learning approaches, that include both ways of supervised and unsupervised learning being heavily dependent on feature extraction; and deep learning approaches where algorithms extensively make use of neural networks.

Yadav. A, and Vishwakarma. DK, (2020) The author had rather broadly deep learning models, including convolutional neural networks, recurrent neural networks, and long short-term memory networks. The authors have elaborated on the strengths and limitations of the models in this context when dealing with huge datasets, pointing out that it is not only performing better for the underlying information but that they also handle large datasets easily compared to traditional methods.

Zhu. L, et al (2023) A detailed overview had shown of the techniques on multimodal sentiment analysis, focusing mainly on methods for the integration of data from multiple sources, such as text, audio, and video. In the paper, different fusion methods that include early, late, and hybrid fusion were classified and evaluated. Their respective strengths and challenges were discussed. Important challenges can be summarized as handling heterogeneity in data, feature alignment between modalities, and managing increased computationalcomplexity.

Zhang. W, et al (2022) This survey had shown a comprehensive survey about the area of Aspect-Based Sentiment Analysis. It puts forward three primary tasks in ABSA: aspect extraction, sentiment classification, and aspect-sentiment co-extraction. The authors survey methods applied to ABSA, including rule-based methods and machine learning and deep learning techniques; their efficiency and limitations are addressed. This survey also points out the necessity of having high quality annotated datasets and more advanced models that approach human complexity in language

METHODOLOGY:

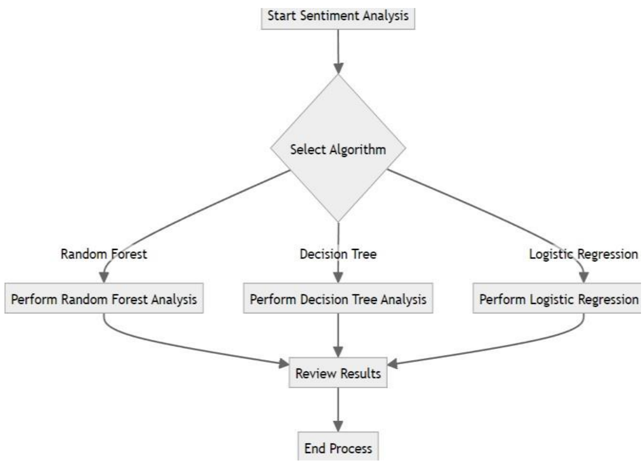

Fig.1 Methodology Model

Data Collection

Here in fig.1 the methodology model has been shown with the sub-division part along with the algorithms i.e. Random Forest, Decision tree and logistic regression Sentiment analysis starts with data collection and this is the most important part. In the case of Twitter sentiment analysis, one should collect large volumes of tweets relevant to the area of concern. With the Twitter API, researchers can programmatically grab the tweets as one needs them, fired by pre- specified criteria like some keywords, hashtags, or user mentions. For example, in public sentiment analysis concerning a new product, the name of the product, hashtags related to it, or the company being talked about are all parts of the tweets that are collected. Also, there is control over the time window setting for data collection, and this can make one very selective with respect to holistically specific periods, say during a product launch or some ongoing event. One of the essential attributes toward this regard would be gathering a diversified dataset that incorporates a vast range of opinions and sentiments to ensure that the analysis is comprehensive and therefore unbiased.

Data Pre-Processing

Every sentiment analysis starts with a pre- processing step, in which the data source is bound to be social media, with mostly unstructured and noisy tweets. Pre- processing is a way of cleaning text data to allow it into the machine-learning models. Typically, it initializes by cleaning text: unwanted characters such as URLs, mentions, special symbols, are removed. This brings analysis on the granularity of words themselves in the text. Many tweets contain a rich set of emojis and slang. Emojis can carry significant sentiment information, so instead of removing them, they are often converted into corresponding text descriptions. By addressing these aspects, the pre-processing phase ensures that the data is in a clean, consistent format, ready for feature extraction and further analysis.

Feature Extraction

Feature extraction is done through processing the pre-processed text with numerical inputs integrated into the machine learning algorithms which communicate through their real-valued process. This is important in that the major procedure for machine learning requires the use of numeric input rather than the raw text.

One of the techniques that is more commonly used to overcome this limitation is called Term Frequency-Inverse Document Frequency, or TF-IDF. It does not just consider the frequency of words; instead, it scales these frequencies by how common or rare that word is

in a dataset. This will favour words that are important in specific tweets and lower the significance—that is, the importance used in more advanced applications of sentiment analysis when understanding the context and semantics of a particular word is very important. These methods create a kind of dense vectors in a continuous vector space, which manage semantic relationships between words to derive meanings from context.

Modelling

Modelling means training the cleaned-up data using machine learning or deep learning models for sentiment prediction. Features from textual data are fed into various previously chosen models in view of specificanalysis requirements.

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- Random Forest: This technique of ensemble learning is very popular. It creates many differently trained decision trees and enables them to vote for prediction with more accuracy and stability. It performs effectively on large volumes of data with complex features, making it fit for tasks like sentiment classification.

- Logistic Regression: A statistical model that makes use of a logistic function in modelling binary dependent variables; Logistic Regression is applied in classifying tweets as either positive or negative sentiments. This model is very easy yet powerful if the relationship between features and the target variable is linear.

- Decision Tree: It is a decision modelling algorithm that models' decisions and their possible consequences, including the outcome of chance events and resource costs, as a tree structure. Every node represents features that are associated with branches, which symbolize the decision rules, while the leaves are the class or outcome. Its ease of use and interpretability components have made it very popular in sentiment analysis, more so with categorical data.

Model Training & Evaluation

In the next step, the proper models should be trained using the dataset, and their performance measured thereafter. During training, it learns from the labelled data the tuning of parameters in a way so that there is as little misclassification of sentiment as possible. Cross-validation methods guarantee the generalizability of the models to new data. Some other metrics, like accuracy, precision, recall, and F1 score, are used to check the model after training. These measures tell a lot about how well the model is working and fine-tune it for better results. The testing will be done on a different test dataset to know if it works efficiently in every real-world situation.

Results:

To gain more insight into the nature of expression of the sentiments through the tweet, a detailed analysis of the most common words has been presented for each category of expression of sentiments:

PositiveTweets:

Positive tweets will carry expressions of happiness, satisfaction, and appreciation. They usually dwell on favourable opinions and views regarding experiences, events, products, or services in which customers can feel content and happy. Language in tweets very enthusiastic and largely optimistic includes words such as "happy," "love," "great," "amazing," and "fantastic" Used in fig.2 the graph with the numbers which are at maximum and minimum times been there. Most of these positive tweets imply some momentous successes, like personal achievements in soccer. In other positive tweets, they include kudos to products and services that have met or surpassed their expectations. In fig.3 the word cloud has been made to make it understandable the words according to the highest ranking from the graph shown in fig.2 Such positive tweetsreflect real pleasure and satisfaction.

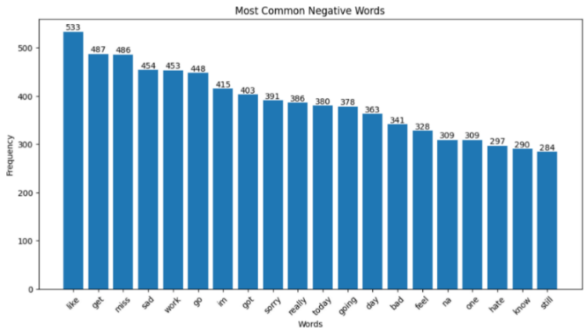


Fig. 2 Most common positive words

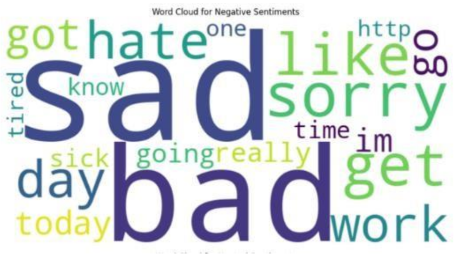


Fig 3. Positive SentimentsNegative Tweets:

Negative tweets are marked with expressions of dissatisfaction, frustration, or criticism. Usually, users are expressing their disliking or frustrations over certain issues, products, or services, and the language is more critical and emotive. Here in fig. 4 Some commonly occurring terms in such tweets include "hate," "angry," "disappoint," "frustrated," and "terrible," indicating the level of negativity from users has been shown in the numbers with moat used. These critical tweets have a linguistic intensity and emotional density, marking off areas of discontent to give valuable feedback and reflection on bigger concerns related to the subject under question. Fig.5 shows the negative sentiments through word cloud according to the highest and lowest words which are used in common. It is in such expressions of frustrations that a related difference in the issues or brand perceptions is created.

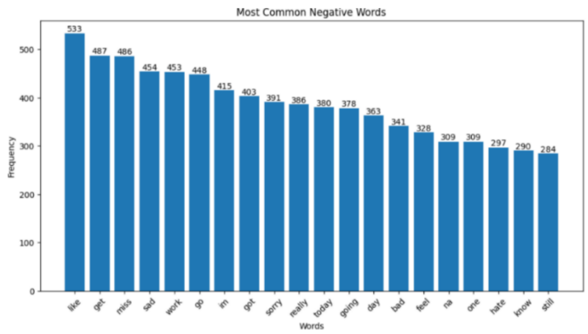


Fig.4 Most common negative words

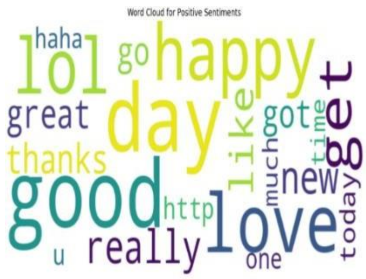


Fig.5 Negative SentimentsNeutral Tweets

Neutral tweets are indicative of the expressions that present the mention of facts or any updates but do not emanate any kind of strong emotions. In general, this may be used to report news, give updates, or provide information without showing directions of obvious persuasion of positive or negative stance toward the topics. In fig. 6 the most common words sucg as “get”, “day”, “work”, “back”, etc. are used with the graph and the maximum and minimum numbers the number of times it has been repeated. Words in neutral tweets should be objective and informative to ensure the passing of information with less vocal persuasion and in a simple and impartial manner, if informative as opposed to argumentative approaches are desired. Now in fig.7 the word cloud had been shown for neutral sentiments through the analysis done by the number of commonwords used.

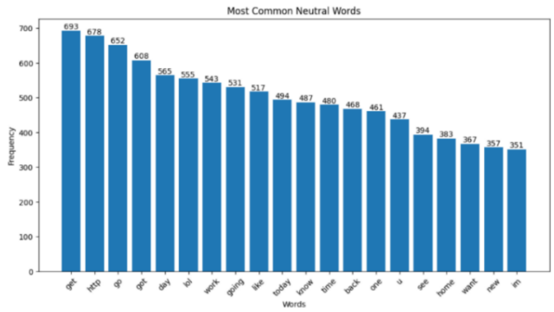
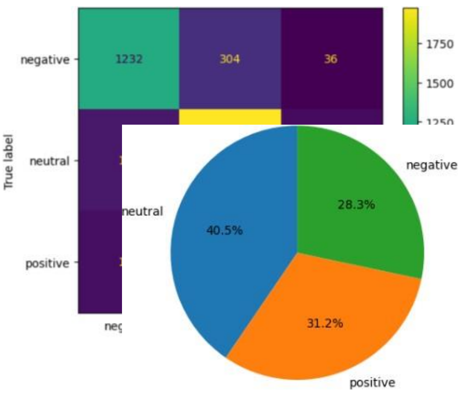


Fig 6. Most common neutral words

Fig.7 Neutral Sentiments Word Frequency Analysis:

In doing so, we considered positive, negative, and neutral tweets for finding common linguistic patterns related to each class of sentiments in our sentiment analysis. The word frequency analysis is one ultra-helpful action concerning general themes or topics of prevalence in a dataset. High- frequency words under the positive tweets are "happy," "love," "good/great," "amazing," and "fantastic," indicative of an optimistic and enthusiastic mood. Here in fig.8 the overall sentiments for positive negative as well as neutral has been used through the samples as well as the counts and thus it has been analysed according to words which goes to one of the sentiment part out of three. In most cases, these words showed the satisfaction, contentment, or joy of users, mostly in contexts such as personal achievements, product reviews, and events. Epitomized by these terms are the dissatisfaction, criticism, and frustration by users about unsatisfactory experiences or issues against services or products.



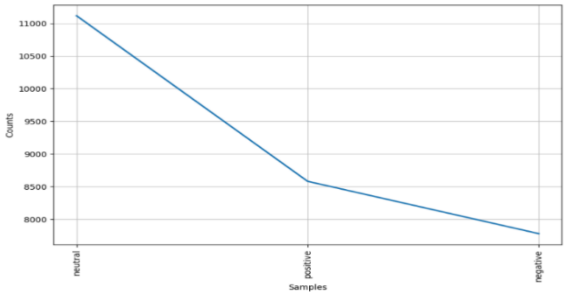


Fig. 8 Word Frequency Model withSamples

Baseline Model: A baseline model was first developed to provide a point of reference against which to compare the performance of the more sophisticated algorithms in sentiment analysis. In this, an accuracy of 40% is indicated in the base model.

Logistic Regression:

Logistic regression model was at about 83% in accuracy way above that of the baseline model, which had an accuracy of 40%. Here in fig.9 through confusion matrix of all three sentimental analysis has been shown as well as the classification report which shows recall, precision, f1-score as well as support. This improved performance of the model underlines how good logistic regression is at classifying positive, negative, and even neutral sentiment from tweets. Logistic regression is a statistical method for modelling the probability of a binary outcome dependent on one or more predictor variables. It demonstrates how strong and dependable the model is in handling involved complexity about the expression of sentimentand resultant tweet classification.

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	precision	recall	f1-score	support
negative	0.81	0.78	0.80	1572
neutral	0.79	0.88	0.83	2236
positive	0.91	0.80	0.85	1688
accuracy			0.83	5496
macro avg	0.84	0.82	0.83	5496
weighted avg	0.84	0.83	0.83	5496

Fig.9 Confusion Matrix model with classification report

Decision Tree Classifier:

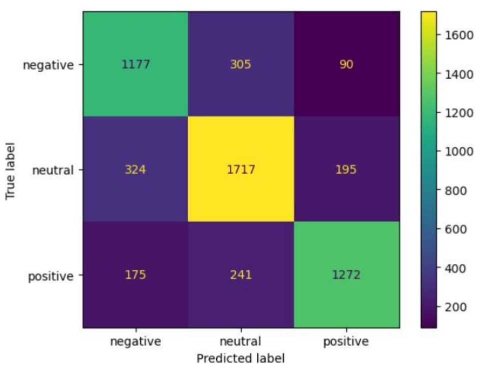
It contributed a lot to improvement over the baseline model but less effective compared to the logistic regression one. Here in fig.10 for decision tree the confusion matrix for the labels has been shown for predicted as well as true and in the classification report has been shown including all the components features with the accuracy reaching upto 76%. In a recurrent fashion, decision trees aremeans divided into sequential subsets based on ordered feature values in the construction of the tree as a decision structure. It provides better accuracy than the simple models due to its capability of capturing nonlinear relationships in data. This model sometimes faces Overfitting issues, leaving poor generalization to newly seen or unseen data, especially if it is too complex

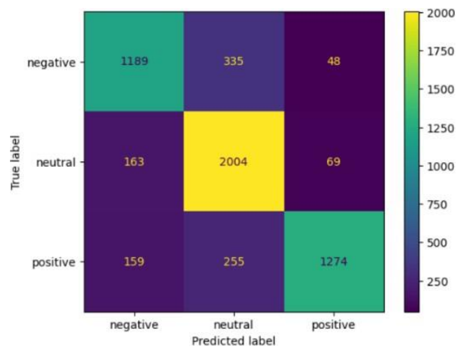
	precision	recall	f1-score	support
negative	0.70	0.75	0.72	1572
neutral	0.76	0.77	0.76	2236
positive	0.82	0.75	0.78	1688
accuracy			0.76	5496
macro avg	0.76	0.76	0.76	5496
weighted avg	0.76	0.76	0.76	5496

Fig.10 Confusion Matrix model with classification report

Random Forest Classification:

Random forests improve basic decision trees by using many decision trees. In the fig.11 the random forest gets the accuracy around closer to logistic regression as well as the confusion matrix included all the three positive, negative, and neutral sentiments. Here the accuracy through the classification report including also the other components can be shown where the accuracy report goes to 81%. It is a way to train many trees on different subsets of data following strategies like bagging or random forest and aggregating predictions of trees in many ways, hence reducing bias and variance components of individual model classes. It is because through combination, it captures wide diversity and complexity in sentiment data, hence better terms of accuracy and robustness.





	precision	recall	f1-score	support
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neutral	0.77	0.90	0.83	2236
positive	0.92	0.75	0.83	1688
accuracy			0.81	5496
macro avg	0.83	0.80	0.81	5496
weighted avg	0.82	0.81	0.81	5496

Fig.11 Confusion Matrix model with classification report

Conclusion:

Actually, a good number of these machine learning algorithms are very effective in classifying tweets into the categories of positive, negative, and neutral sentiments. Our first model where we built off with our baseline model consequently returned an accuracy of 40%. Of these, logistic regression was the most resilient model, with an accuracy that could go as high as 83%. If compared to the baseline, decision tree classification improves upon it with an accuracy of 75% but raises concerns about possible overfitting and dependence upon the particulars of the data. On the accuracy front, for Random Forest Classification was very strong as a representation of ensemble methods for gaining diversity in the patterns that were to be captured within the data and thus would sustain balance or reliability regarding classifying sentiment with accuracy of 81%. The words reflecting joy and satisfaction prevailed in positive tweets, negative tweets by terms posing dissatisfaction and frustration, while neutral tweets only used terms focused on factual reporting.

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