iKSP Journal of Computer Science and Engineering
http://iksp.org/journals/index.php/ijcse/index

Mental Health Diseases Analysis on Twitter using Machine Learning

Mehak Faryal*[1], Muhammad Munwar Iqbal[1], Hifsa Tahreem[1]
[1]Department of Computer Sciences, University of Engineering and Technology, Taxila, Pakistan
[2]Facoltà di Ingegneria Dell'informazione,informatica e statistica sapienza università di Roma, Rome, Itlay

---

Abstract - Twitter is a cutting-edge platform among social networks. It allows microblogging of up to 140 characters for a single post. Due to this feature, it is popular among users. People tweet on a variety of topics, from everyday events to major accidents. Twitter Attitude Analysis gives organizations the ability to screen audiences' behaviour concerning related products and events in real-time. The first step in attitude analysis is the processing of Twitter data before the text. It uses a Twitter dataset that makes NLTK resources available to the public. Most of the existing research on Twitter attitude analysis focuses on removing mood traits. However, the pre-treatment method is used for selection. This study discussed the effect of the word processing method on mood classification. The performance measured in two types of classification activities and summarized. The classification performance of pre-processing methods using different attributes and classifiers in the Twitter dataset retrieved from Twitter Application Programming Interface API. The pre-processing used to remove URL's removing meaningless numbers or words. Therefore, Twitter data is extracted, and the mood is calculated for tweets on a particular topic. It focuses on tweets about mental health problems caused by the use of social media platforms. We calculate and analyze attitudes from tweets using machine learning algorithms. We implement the machine learning algorithms, including Naive Bayes, Random Forest, Regression, and support vector machine. The results show that classification accuracy improves Twitter F1 ranking while using pre-processing methods to expand acronyms and replace negligence. The function extraction methods are combined with Machine Learning algorithms were found to have the highest accuracy of 92%.

Keywords: Mental health; ethics; machine learning; algorithms; social media

---

INTRODUCTION

As mobile internet demand has increased in recent years, microblogging has changed to a new social networking website for the public, which is now a social tool that people use every day. On Twitter, thousands of people use it to express their opinions, suggestions, or feelings on any hot topic. The subjectivity of the Twitter news posted by the users applies to everything related to them and real-life issues, which contains a lot of information. More and more institutions are using mindset information for analysis and discovery to make decisions and evaluations for the future. Twitter is the most popular source of data for user thoughts and emotions expressed on this platform and can be extracted easily and analyzed. Social networking sites changing lives and the purpose of interaction or connection with the world (Dos Santos & Gatti, 2014). Recent research shows that a large number of people use social networking services such as Facebook and Twitter for a variety of purposes such as finding and sharing data, making and joining friends, making friends, and having fun. A social network is an online tool that enables the user to register themselves with a unique id(username) to interact with new users, chat with users, share events, photos, and videos on one social platform (Cambria, 2016). New users often turn to users who recommend users who are already using this platform. However, as their experience grows, they become friends with relatively different people with similar interests. This can be seen on Facebook and Twitter.

*Corresponding author:
Email: mehak.faryal@students.uettaxila.edu.pk (M. Faryal), munwar.iq@uettaxila.edu.pk (M.M. Iqbal)
tahreem.1874105@studenti.uniroma.it (H. Tahreem)

New people follow standard users and their friends on Twitter before gaining enough trust to choose others more carefully based on similar interests. One of the main advantages of social media is that it can give us meaning to other users, and the largest shared data on social networking sites useful for analyzing the required situation and predicting the future (Flesca, Greco, Masciari, & SaccÃ 2018).

RELATED WORK

Mental health problems such as depression, suicidal ideation, or post-traumatic stress disorder (PTSD) The author has implicit information about the user in a text on social media, modeled in Natural Language Processing (NLP) to predict traumatic characteristics. User as a personality and age mode for life and sex. Similar text messages have been used effectively for divination. Recent research has successfully used social media data to predict people's mental health, from the presence and severity of mental disorders such as depression to suicide risk (CHANCELLOR, BIRNBAUM, CAINE, SILENZIO, & DE CHOUDHURY, 2019).

Online anti-social conduct is a social problem and a risk to public health. Establishing such behavior can be pleasurable to harassment but can lead to depression, self-control, low self-esteem, anxiety, anger, and intervention. These backings a more proactive methodology was dependent on regular language handling and AI that will permit electronic stages to effectively search out indications of solitary conduct and intercede before it separates. By effectively searching for such practices, long range interpersonal communication locales can dodge genuine cases that can prompt suicide. Self-destructive contemplations of the time and web stages like Twitter and Facebook can be favorable places for such conduct. These stages may have set up to debilitate introverted conduct on the web. However, this conduct is as yet common. Most measurements depend on client references to stages to communicate their sentiments and feelings (Singh et al., 2019). Tweep's system allows the consumer to analyze the state of depression using machine learning based on personal messages from Twitter. To prevent the consumer from suffering from mental illness, Tweep analyzes the personal state of depression of Twitter users and the state of the people they follow on Twitter, that is, their “next”. This project is the first attempt to implement an Interface System that analyzes depression for the public. The system uses Vader’s rules-based download analysis and two machine learning techniques, namely Naive Bayes. System output is the percentage of positive and negative posts from Twitter users and their followers (Razak et al., 2020) .The optimism of suicide in social media is new concerning the territory of examination as it contains extraordinary issues. In the current review, that openly accessible data spread via web-based media stages is an important marker for viably distinguishing individuals with self-destructive expectations. The fundamental test in suicide avoidance is understanding and revealing the mind-boggling hazard factors and cautioning signs that can trigger a mishap. In this article, web-based media stage clients find a better approach to utilizing Twitter stages to assemble the alerts of suicides in individuals and distinguish presents containing content related to self-destruction. This methodology contains the main curiosity is the programmed ID of abrupt changes in client conduct on the web. To identify such changes, the blend of characteristic language preparing methods to gather and interpret conduct and literary properties into a martingale structure is applied, which is generally used to recognize changes in information streams. Investigations show that the methodology is to message documentation successfully catches cautioning signs in content contrasted with customary AI arrangements. The Martingale system's usage features changes in online conduct and shows a guarantee of identifying social changes in individuals in danger. As a World Health Organization (WHO) study, 800,000 individuals kick the bucket because of suicide endeavors. Screen a client's emotional well-being on Twitter. Expanding on existing exploration, the work on deciphering and evaluating self-destruction cautioning signs in an online setting of Twitter client acted as a flood of perceptions and utilized a martingale system to reveal purposes of progress in this stream. The experience shows that the way to deal with Natural Language Processing (NLP) text focuses recognizes tweets with speed-related substance and fills in as an amazing voice under the martingale. Since the martingale esteems relate to the line discourse's adjustments, recognizing the change focuses should be discovered, which helps to distinguish the real change point for an approval situation, yet the methodology should be more powerful as far as boundary tuning and positive language changes (Vioules, Moulahi, AzÃ©, & Bringay, 2018). Suicide was the main source of death in the United States. Mental stressors are one of the main sources of self-destruction. Many artificial automated strategies have been proposed to eliminate mental stress users from Twitter. Examine procedures for recognizing self-destructive mental stressors from Twitter utilizing profound learning strategies and an adaptable learning system that uses a current explanation dataset from a clinical book. Use deep learning techniques to identify psychiatric stressors on Twitter. When deep learning is compared to conventional algorithms used for machine learning, the results show that deep learning gives better results than machine learning algorithms. Convolutional neural network CNN is a leader in identifying suicide-related tweets with 78% accuracy and an 83% F-1 calculation, Support Vector Machine (SVM), surpassing Recurrent neural network RNN-based recognition of psychiatric stress, the best calculation. F -1 of 53.25%). Moreover, clinical notes' interpretation of the Twitter corpus outperforms the Twitter corpus preparation, yet with an F-1 estimation of 54.9% by the exact incident. From the outcomes, it very well may be inferred that it is gainful to utilize deep learning strategies for programmed pressure location in online websites (Du et al., 2018). Behavioral psychopathology shares that anxiety and depression are closely related and anxious depression is defined as a mental condition of people diagnosed with depression present in a continuously stable manner with feeling anxious instead of sad. It is a main depressive disorder) with a co-morbid anxiety disorder. Basically, there are two anxiety disorders, one is a temporary anxiety disorder, and the other is character anxiety. The study of anxiety is an interesting and interesting fact since anxiety exists as a condition and characteristic and as a state of anxiety. Temporary anxiety is the condition in which the person is temporarily affected by the current situation in which the interviewee notices how they currently feel at that moment, and the anxiety symptoms are defined as "a general tendency to be anxious when the interviewee You feel it How do you usually feel? (Gruda & Hasan, 2019).There are currently over 6,000 rare diseases, and their patients are increasing.

Currently, most research is based on diagnosis and development, and limited surveys work on themes and emotions that these are very little amount patients who express their feelings on social platforms, exclusively in online health communities (OHC). Different techniques used to find that in how many categories the sentiments are divided, following techniques were used latent Dirichlet, Naive Bayes algorithms and Concept Frequency-Inverse document frequency, with the help of a tool named Gephi tool used to analyze the growth in society, with the help of sentiment analysis health care professionals says they get a better understanding between patient experience and needs, yet this work is done on a small scale yet, more will come to study depends on a number of patients (Bi et al., 2020).Online media have enabled gigantic amounts of people, wherever, from any section gathering, to impart time-ventured messages on any subject, in any language, and with essentially no channel. The Pew Social Media Reality Sheet disseminated in 2017 revealed that around 70% of the general population in the United States adequately uses online media, and the customer base is seeing endless advancement around the world. Their past investigation recommended that "prosperity and drug" is one of the most standard topics of discussion in online media, with 37% of adults recognizing it as the most interesting subject. Because of the presence of tremendous proportions of prosperity related information, it is as a result, logically utilized as a data hotspot for checking prosperity examples and ends. The online media traffic is being used or considered for a few, prosperity-related applications, such as general prosperity checking, following disease outbreaks, diagramming conduct factors, such as smoking, reacting to enthusiastic prosperity issues. The electronic media rebellion has coordinated with remarkable movements in the fields of customary language getting ready Natural Language Processing (NLP) and data examination, and, inside the prosperity space, biomedical data science. However, notwithstanding late advances, performing complex prosperity related tasks from online web platforms isn't minor.(Sarker et al., 2018)

The investigations of AI and emotional well-being that utilized electronic wellbeing records (EHRs), temperament rating scales, mind imaging information, novel observing frameworks (e.g., cell phone, video), and web-based media stages to anticipate, order, or subgroup psychological wellness ailments including gloom, schizophrenia or other mental sicknesses, and self-destruction ideation and endeavours. On the whole, these investigations uncovered high correctness's and gave fantastic instances of artificial Intelligence AI's potential in mental medical services, yet most should be viewed as early evidence of-idea works showing the capability of utilizing artificial intelligence AI Machine Learning (ML) calculations to address emotional well-being questions, and which kinds of calculations yield the best presentation. (Graham et al., 2019) As of late, wellbeing web-based media have connected an ever-increasing number of individuals to share their own sentiments, conclusions, and involvement with the setting of wellbeing informatics, which has drawn expanding consideration from both scholarly world and industry. This paper centres around the conduct impact investigation dependent on heterogeneous well-being information created in online media conditions. A coordinated neural organization based learning model is intended to break down and portray the dormant conduct impact covered up across different modalities, in which a convolutional neural organization based structure is utilized to extricate the time-arrangement highlights inside a specific social setting. The scholarly highlights dependent on cross-methodology impact examination are then prepared in a SoftMax classifier, which can bring about a rebuilt portrayal of significant level highlights for online doctor rating and characterization in an information driven way. At long last, two calculations inside two agent application situations are created to give patients customized proposals in wellbeing web-based media conditions. Examinations utilizing this present reality information exhibit the adequacy of our proposed model and strategy(Zhou, Liang, Kevin, Wang, & Shimizu, 2019) . A developing collection of exploration is associating web-based media information with AI and Machine Learning to foresee people's emotional well-being conditions. The implications of this examination lies in educating proof based conclusion and treatment. In any case, acquiring clinically legitimate demonstrative data from delicate patient populaces is testing. Therefore, scientists have functioning trademark online practices as "intermediary analytic signs" for building these models. This paper places a test in utilizing these analytic signs, suspected to help clinical dynamic.

Zeroing in on three usually utilized intermediary symptomatic signs got from web-based media, we locate that prescient models based on these information, albeit offer solid interior legitimacy, experience the ill effects of helpless outer legitimacy when tried on psychological well-being patients. A more profound jump uncovers issues of populace and inspecting predisposition, just as of vulnerability in build legitimacy intrinsic in these intermediaries. We examine the methodological and clinical ramifications of these holes and give therapeutic rules to future examination. R13 Natural language processing (NLP) procedures can be utilized to cause deducing about people groups' psychological states from what they to compose on Facebook, Twitter and other web-based media. These deductions would then be utilized to make online pathways to guide individuals to well-being data and help and produce customized intercessions. Unfortunately, the computational strategies used to gather, measure and use web-based composing information, just as the assessments of these procedures, are as yet scattered in the writing. This paper gives a scientific categorization of information sources and strategies that have been utilized for psychological wellness backing and intercession. In particular, we audit how online media and other information sources have been utilized to distinguish feelings and recognize individuals who might be needing mental help; the computational strategies utilized in naming and determination; lastly, we examine approaches to produce and customize emotional well-being mediations. The overall point of this perusing audit is to feature regions of examination where Natural language Processing NLP has been applied in the psychological wellness writing and to help build up a typical language that draws together the fields of emotional well-being, human-PC cooperation, and Natural language Processing NLP (Ernala et al., 2019).

Suicide is among the 10 most normal reasons for death, as surveyed by the World Health Organization. For each demise by suicide, an expected 138 individuals' lives are definitively influenced, and practically some other measurement around suicide passing is similarly disturbing. The inevitable of online media and the close omnipresence of cell phones used to get to web-based media networks offer new sorts of information for understanding the conduct of the individuals who endeavour to end their own lives and proposes additional opportunities for preventive intercession. We show the achievability of utilizing online media information to distinguish those in danger of suicide. In particular, we utilize regular language handling AI and Machine Learning procedures to identify quantifiable signs around suicide endeavours and depict plans for a mechanized framework for assessing suicide hazards, usable by those without specific emotional well-being preparing. We additionally talk about the moral utilization of such innovation and inspect security suggestions. Presently, this innovation is just utilized for mediation for people who have "picked in" for the investigation and intercession, yet the innovation empowers adaptable screening for self-harm hazard, possibly recognizing numerous individuals who are in danger preventively and preceding any commitment with a medical care framework. This brings up a critical social issue about the compromise among protection and anticipation we have conceivably life-saving innovation that is presently arriving at just a small amount of the potential individuals in danger due to regard for their security. The current compromise is among security and counteraction the correct one (Calvo, Milne, Hussain, & Christensen, 2017). Web-based media has become a piece of everyday correspondence in public activity. Twitter is one of the microblogging destinations which is utilized worldwide for associating with each other. These days psychological wellness is likewise a primary issue in the general public. We recognize the psychological well-being of an individual utilizing AI draws near, the information assortment is finished by Twitter API utilizing enthusiastic watchwords, and classifier is worked for examination utilizing two classes to arrange the extremity of tweets (Coppersmith, Leary, Crutchley, & Fine, 2018; Malik, H. A. M. et al., 2021).

Online media has become a space for people to pass on their perspectives, contemplations, and feelings freely on various current issues. Twitter is a mainstream writing platform, which is one of the broadest correspondence stages. We examine the psychological wellness of an individual utilizing tweets that were removed depending on passionate watchwords. Estimation investigation of tweets is completed utilizing machine learning-based calculations like Support Vector Machine (SVM), and Naive Bayes calculation to characterize an individual's emotional wellness dependent on their natural prosperity. People share their emotions, sees, assessment through different Microblogging locales these days. Innovation has caused progress in the manner people to interface with one another officially or casually. Through its different channels, web has empowered people to share their delights, distresses, disillusionment, and sentiments with the world. One such stage is Twitter, which has many clients who offer tweets on various points (Rakshitha & Gowrishankar, 2018).

System Model

This section discusses the idea of the proposed framework that is described in Figure 1, which describes the steps of sentiment quantification. First step is collection of Datasets and after collection of datasets, pre-process of these datasets will be performed twitter API and using hashtags , we use hashtags related to depression and anxiety .i.e. stress", "depression", "mental illness", "anxiety”, “bipolar", "social anxiety", "depressed mood” "feeling low", "feeling depressed", "lost interest", "hopeless", "suicidal thoughts", "sad" ,"hate ","kill", "emotionally weak", "bipolar disorder",

"pstd","mental "mental health", "mental health awareness", "medicines for depression", "lack of concentration", "Twitter depression", “Mental. We use python for coding purposes and code executed in the jupyter notebook.
Afterward feature engineering of these processed datasets will be performed using equations shown below in section Results and Discussion. All these words in tweets are characteristic of depression. Further, we explain with the help of the system model can be seen in Figure 1.

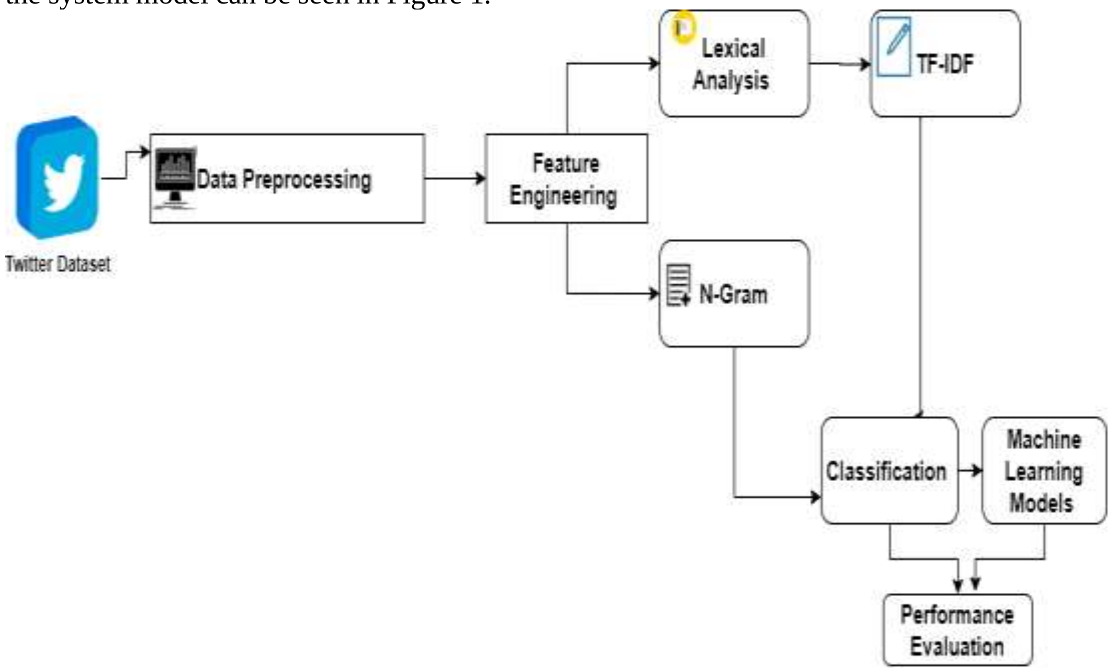

Figure 1: The Proposed system methodology for analysis

After extracting features from these pre-processed data sets, these extracted features are fed to different classifiers for classifying them in classes. After classification, the next step is a quantification of the dataset. After quantifying data, different performance evaluation measures will be applied to evaluate the proposed method's performance.
For this research, all development is done Jupyter notebook 2017 Data Preparation, Feature extraction, and classification tasks are performed using a variety of python packages. All classifiers were used sci-kit and Natural Language Processing (NLP) package. Classifiers were trained using 10-fold cross-validation to avoid Over-_fitting and then tested on a held-out test set. For the test set only presented recall, precision, and f-measure of the positive class. Datasets are to be used for experimentation purposes, techniques to be used, and evaluation measures for evaluating performance.
Data set is extracted from Twitter using Twitter API, Almos16,581 Tweets gathered. After the acquisition of data next step is pre-processing of data. To pre-process data sci-kit library is used different data pre-processing techniques using Natural Language Processing NLP. Features are divided into two sets: lexical features and Word embedding. Lexical features include Term Frequency- Inverse Document Frequency TF-IDF and for word embedding features, include n-gram.
Term Frequency- Inverse Document Frequency (TF-IDF) is a technique including Bag of Words and n-gram depends on word embedding. In Term Frequency- Inverse Document Frequency (TF-IDF) alongside the N-gram approach, the first n-grams highlight extraction method is applied on the dataset. By applying n-gram on dataset word list from both information is gotten. After n-gram Term Frequency- Inverse Document Frequency (TF-IDF) is applied on information to get term recurrence converse archive recurrence of these word lists from datasets.

$$TF - IDF = TF * IDF$$

We divided the dataset to keep user's data for the training set and for the test set from the Users dataset. As we are using Sci-kit learn library throughout the process same is used for the training and testing, use the model sklearn.model_selection.train_test_split Train and test size are 0.7 for training and 0.3 for testing. We have used the following machine learning-based algorithms.

- Logistic Regression.
- Support Vector Machine(SVM).
- Random forest.
- Multinomial Naïve Bayes.

RESULTS AND DISCUSSION

In this section, we demonstrate the results and discuss them in detail. First of all, extract tweets from Twitter using Twitter *Application Programming Interface (*API*)*. Almost 33,162 tweets were obtained from Twitter. After applying pre-processing and cleaning, it comes to almost 16,581 tweets. Analyzing tweet data by applying pre-processing techniques on text data, the cleaning process includes the following steps

1. Punctuation Removal
2. Tokenization - Converting a sentence into a list of words
3. stop word Removal
4. Stemming/Lemmatization – convert word to its root word

We apply descriptive data analysis by using functions, and we categorize the obtained tweets into three groups, which can be seen in Figure 2. There are three class labels to predict positive, negative, and neutral. Below diagram shows the sentiments on the x-axis and count on the y-axis .i.e. how many times positive, negative or neutral sentiment exists in tweets that we collect from twitter.

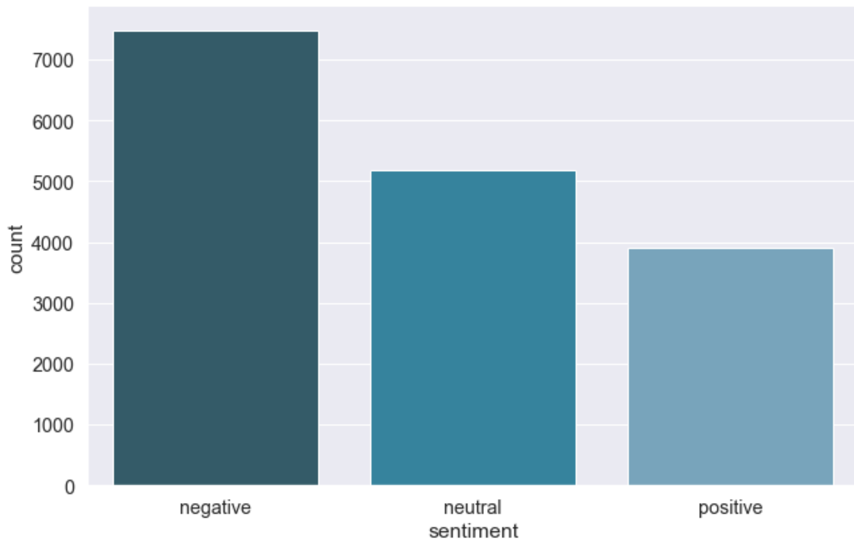

Figure 2: Sentiment Count of the extracted tweets.

Word frequency, the number of times used in the tweet by the user, or how frequently the word is being used in the given data are shown below in the following word frequency graph in Figure 3.

We get the mental features that have the highest frequency, and then there is the word depress, health, stress, like, anxiety, talk. We want to order soon, emot (as in emotion), and pa, order, ill, away, and sad.

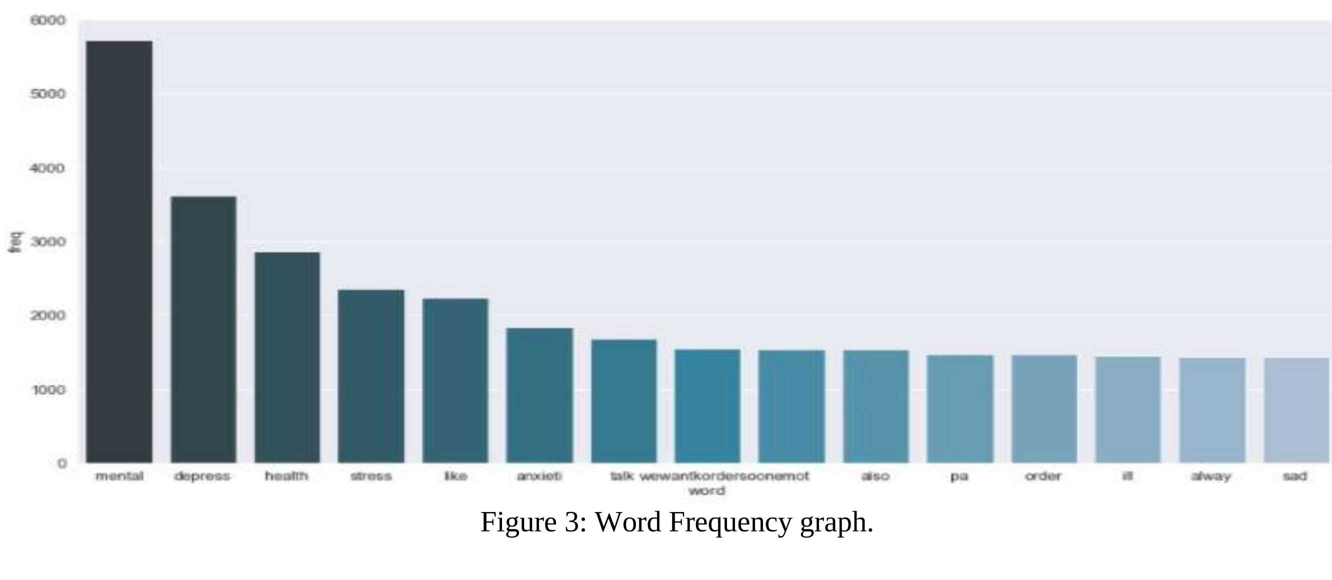

Figure 3: Word Frequency graph.

Whenever text data is classified, word cloud must easily see the positive, negative, and neutral results. Word clouds are created by installing the word cloud library in python. Different colors and sizes show the frequency and importance of that word. All mental health-related sentiments gathered in this word cloud. They are all Positive, Negative, and Neutral, which can be seen in Figure 4.

Figure 4. Word cloud: All the sentiments shown in this cloud, including positive, negative, and neutral.

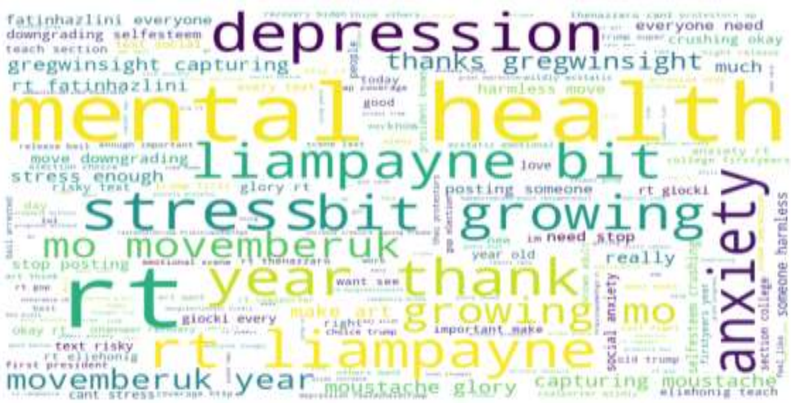

Figure 5. Word cloud showing the positive sentiments.

We gather the text data from tweets that users send. We extract the most used positive words from the tweet and make a word cloud of positive Tweets data that is in text form. Different colors and sizes show the intensity and Frequency of the word in the word cloud. Different packages are installed to produce the word cloud from the data. Pandas, NumPy, word cloud, matplotlib installed to get the required results after cleaning the data. Positive data are shown in the figure below for the mental health disease in the word cloud below in Figure 5.

We visit the social network that is Twitter, and data-driven is through hashtags it is obvious that positive and negative sentiments must be attached in the text. We collected the negative tweets and made a word cloud. All the negative sentiments are shown in the below word cloud related to mental health disease and mental health disorder, which can be seen in Figure 6.

Figure 6: Word cloud showing negative sentiments.

The following graph shows the accuracy of Machine learning models on the y axis in the form of numbers and model name on the y- axis like which model we trained our mental health data shows how much accuracy. It is shown in the following graph in Figure 7. It concerns with respect to the index and number of folds for the indexing of cross-validations. According to the graph below, the highest accuracy is shown by linear Support vector machine (SVC), i.e., 0.9, and the lowest accuracy is 0.5, that is, the Random forest model. Accuracies of other models on which we trained our data set that we extracted from Twitter as of people opinions and sentiments on the following hashtags of mental health, like depression, anxiety, stress, and other related, can be seen in the graph below.

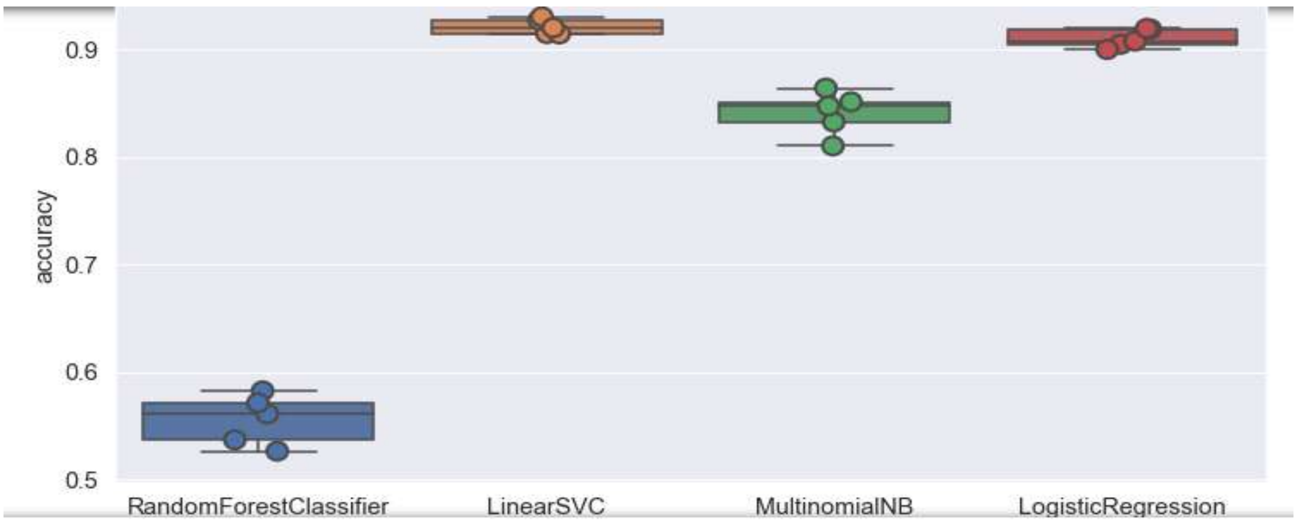

Figure 7: Machine Learning algorithms and Accuracies.

Confusion Matrix is used to evaluate the classification models, and here we classify the Twitter data through a machine learning algorithm, i.e. (Support Vector Machine)SVM. This confusion matrix is created by using the Scikit library in python. Here can be seen that either a person is tweeting positive, negative, or neutral tweets. The diagnol is showing the true positive results. This shows that 2359 sentiments are negative that we get to know from their tweets, data shows data contains the depression-related words, which is negative. The confusion matrix of the highest accuracy machine learning model that is linear Support vector (classification)machine (SVC) can be seen in the matrix form below in Figure 8.

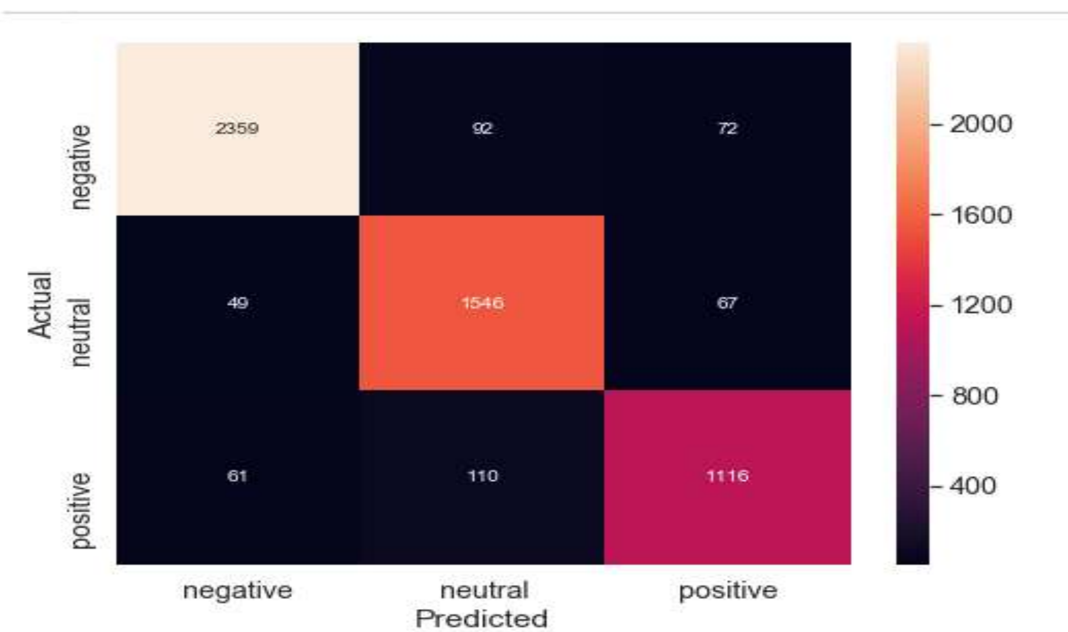

Figure 8: Confusion Matrix for the SVM Algorithm.

Machine Learning algorithms and their mean accuracies are shown in Table 1 below.

Table 1: Machine Learning & their Accuracies

Serial No.	Machine Learning Algorithms	Mean Accuracy
1	Linear Support Vector Classification (SVC)	0.921
2	Logistic Regression	0.909
3	Multinomial Naïve Bayes	0.840
4	Random Forest	0.555

Some Predictions are seen by putting some tweets in the code after extracting features in the Explanatory data Analysis and Data cleaning process. It shows how they predict them. There are three tweets and all three sentiments can be seen predicted on run time, which can be below.

"A super depressing day on Twitter."
 - Predicted as: 'positive.'

"I am leaving Instagram because it causes anxiety more."
 - Predicted as: 'Positive'

"I can't get the money out of the country."
 - Predicted as: 'Neutral'

"The medicines are working because stress is down."
 - Predicted as: 'Negative'.

The equations use in calculating results are written below. With the help of the following equations, we calculated the precision, accuracy, Recall, and f1 scores.

Accuracy = (Total correctly classify)/ (Total Actual)

Precision = (Correctly predicted)/ (Total predicted)

Recall = Recall = (Correctly classify)/ (Total Actual)

f1 - score = (2 ∗ [precision ∗ recall)/ (precision + recall])

Performance evaluation is calculated by using formulas, we calculated the sentiment's precision, recall and F1 scores using the formulas, which are shown in the Table 2.

Table 2: Performance Evaluation

Serial No.	Sentiments	Precision	Recall	F1 score
1	Negative	0.96	0.93	0.95
2	Neutral	0.88	0.93	0.91
3	Positive	0.89	0.87	0.88

We calculate and analyze attitudes from tweets using machine learning algorithms. We implement the machine learning algorithms, including Naive Bayes, Random Forest, Regression, and support vector machine. The results show that classification accuracy improves Twitter F1 ranking while using pre-processing methods to expand acronyms and replace negligence. The function extraction methods are combined with Machine Learning algorithms were found to have the highest accuracy of 92%.

CONCLUSION

In this research study, we have carried out a thorough study on the Twitter dataset to assess the performance of different feature extraction techniques using Machine Learning Models. The main purpose of using different Machine Learning models is to evaluate how these feature extraction techniques affect the performance of different classifiers in terms of Accuracies. Feature extraction techniques used to extract features are lexical features Term Frequency- Inverse Document Frequency (TF-IDF) and word embedding (N-Gram). These features are selected from the dataset named the Twitter dataset. In order to evaluate the performance of different classifiers are first applied to the dataset. These classifiers use Machine learning-based models, i.e. (Naïve Bayes NB, Logistic regression, Support Vector Machine (SVM), and Random forest (RF)). These algorithms' performance is measured in terms of accuracy, f1 score, precision, and recall. Results have shown that Support vector machines present better results than other ML models. Machine learning is widely used for text analysis and sentiment analysis. This study's main issue is to classify how different features concerning sentiments, which are positive-negative and neutral, affect the opinion and how different opinions came out as a result of one research topic that is mental health illness. It is caused by social networking sites and how people give their opinion on the social networking platform Twitter. ML techniques affect the performance of different classifiers for sentiment analysis of data. Classifiers are compared with each other based on all three sentiment features. Results have shown that N-Gram feature extraction has not produced good results. Term Frequency- Inverse Document Frequency TF-IDF produces the best results on the dataset. Results produced by Term Frequency- Inverse Document Frequency TF-IDF along with N-Gram are much more satisfactory. In the case of other classifiers (Naïve Bayes (NB)), Support Vector Machine (SVM), Random Forest (RF), and logistic regression), best results are produced while using Term Frequency- Inverse Document Frequency TF-IDF and N-Gram as a feature extraction technique Twitter dataset. This shows that the choice of feature extracting technique also affects performance in sentiment Analysis. This study has shown that machine learning, widely used in other fields such as text classification or sentiment analysis of data, is also a good choice for sentiment analysis.

REFERENCES

Bi, Q., Shen, L., Evans, R., Zhang, Z., Wang, S., Dai, W., & Liu, C. (2020). Determining the Topic Evolution and Sentiment Polarity for Albinism in a Chinese Online Health Community: Machine Learning and Social Network Analysis. JMIR Medical Informatics, 8(5), e17813.

Calvo, R. A., Milne, D. N., Hussain, M. S., & Christensen, H. (2017). Natural language processing in mental health applications using non-clinical texts. Natural Language Engineering, 23(5), 649-685.

Chancellor, S., Birnbaum, M. L., Caine, E. D., Silenzio, V. M., & De Choudhury, M. (2019). A taxonomy of ethical tensions in inferring mental health states from social media. Paper presented at the Proceedings of the Conference on Fairness, Accountability, and Transparency.

Coppersmith, G., Leary, R., Crutchley, P., & Fine, A. (2018). Natural language processing of social media as screening for suicide risk. Biomedical informatics insights, 10, 1178222618792860.

Dos Santos, C., & Gatti, M. (2014). Deep convolutional neural networks for sentiment analysis of short texts. Paper presented at the Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers.

Du, J., Zhang, Y., Luo, J., Jia, Y., Wei, Q., Tao, C., & Xu, H. (2018). Extracting psychiatric stressors for suicide from social media using deep learning. BMC medical informatics and decision making, 18(2), 43.

Ernala, S. K., Birnbaum, M. L., Candan, K. A., Rizvi, A. F., Sterling, W. A., Kane, J. M., & De Choudhury, M. (2019). Methodological gaps in predicting mental health states from social media: Triangulating diagnostic signals. Paper presented at the Proceedings of the 2019 chi conference on human factors in computing systems.

Flesca, S., Greco, S., Masciari, E., & SaccÃ , D. (2018). A comprehensive guide through the italian database research over the last 25 years: Springer.

Graham, S., Depp, C., Lee, E. E., Nebeker, C., Tu, X., Kim, H.-C., & Jeste, D. V. (2019). Artificial intelligence for mental health and mental illnesses: an overview. Current psychiatry reports, 21(11), 116.

Gruda, D., & Hasan, S. (2019). Feeling anxious? Perceiving anxiety in tweets using machine learning. Computers in Human Behavior, 98, 245-255.

Malik, H. A. M., Abid, F., Wahiddin, M. R., & Waqas, A. (2021). Modeling of internal and external factors affecting a complex dengue network. Chaos, Solitons & Fractals, 144, 110694.

Rakshitha, C., & Gowrishankar, S. (2018). Machine Learning based Analysis of Twitter Data to Determine a Person's Mental Health Intuitive Wellbeing. International Journal of Applied Engineering Research, 13(21), 14956-14963.

Razak, C. S. A., Zulkarnain, M. A., Ab Hamid, S. H., Anuar, N. B., Jali, M. Z., & Meon, H. (2020). Tweep: a system development to detect depression in twitter posts Computational Science and Technology (pp. 543-552): Springer.

Sarker, A., Belousov, M., Friedrichs, J., Hakala, K., Kiritchenko, S., Mehryary, F., . . . Kavuluru, R. (2018). Data and systems for medication-related text classification and concept normalization from Twitter: insights from the Social Media Mining for Health (SMM4H)-2017 shared task. Journal of the American Medical Informatics Association, 25(10), 1274-1283.

Singh, R., Du, J., Zhang, Y., Wang, H., Miao, Y., Sianaki, O. A., & Ulhaq, A. (2019). A framework for early detection of antisocial behavior on Twitter using natural language processing. Paper presented at the Conference on Complex, Intelligent, and Software Intensive Systems.

Vioules, M. J., Moulahi, B., AzÃ©, J. r. m., & Bringay, S. (2018). Detection of suicide-related posts in Twitter data streams. IBM Journal of Research and Development, 62(1), 7: 1-7: 12.

Zhou, X., Liang, W., Kevin, I., Wang, K., & Shimizu, S. (2019). Multi-modality behavioral influence analysis for personalized recommendations in health social media environment. IEEE Transactions on Computational Social Systems, 6(5), 888-897.