

# The Early Detection and Diagnosis of Mental Health Status Employing NLP-Based Methods With ML Classifiers

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## ABSTRACT

People now communicate on a variety of internet channels on a daily basis. Natural language processing techniques can be used to deduce users' mental states based on textual or spoken information they post on these sites. Using SMS to predict mental health issues is a proactive step toward better treatment. NLP is transforming the way that professionals in the field of mental health assess patients' freedom of expression in order to identify and diagnose mental illnesses. In addition to offering new avenues for research into human attitudes and behaviors, machine learning techniques can be used to recognize the telltale indications and symptoms of mental illness. In this study, we investigate various supervised classifier methods in depth and use natural language processing (NLP) to identify the mental health state from a text message. People experience suffering from several mental diseases, but the most common ones include PTSD, bipolar disorder, panic disorder, depression, stress, and anxiety. We used Decision Trees, Random Forest, K-Nearest Neighbors, BernoulliNB, and Logistic Regression to classify the data for this investigation. In comparison to the other four classifiers, Logistic Regression performs the best in our suggested strategy. The experimental result confirms that more accurate patient data classification can be achieved with the suggested methodology. With a 93 percent accuracy rate, the suggested model was demonstrated to be efficient.

## INTRODUCTION

People used to connect with one another in this age through a variety of social media platforms and chat apps, including Twitter, WhatsApp, SMS on phones, and others. Therefore, it is too difficult to determine someone's emotional condition only by looking at their message. Anybody can recognize negative signals as a sign of mental instability. People are unable to interact positively with others when they are insecure or unable to maintain their regular state. Because of this, the unfavorable message could be interpreted as mental illness.

People give their loved one's beautiful messages when they are having fun or feeling loved. Thus, a positive message could indicate that mental wellness is normal. We used the Emotions dataset, which is based on SMS messages sent by individuals to their friends and family, in our study. We use these data to train our model in order to forecast their mental state. Next, we examine how those supervised algorithms compare to one another. Here, K-nearest Neighbor, BernoulliNB, Random Forest, Decision Tree, and Logistics Regression are employed.

## PREVIOUS WORKS

Natural language processing (NLP) was employed by Raj et al. to enhance sentiment-based classification. Characteristic of Sentiment A vector and the beginning of a word have been employed to increase the validity and dependability of the data for these aims. Several machines learning techniques, including Disambiguation of Words

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and SVM, maximum entropy, and naive Bayes, are typically employed in this study. NLP and WSD are used to improve classification accuracy.[1]

The technology used in this study first gathers data from the social networking site Twitter, which is subsequently cleaned using a number of methods. From the training data, feature vectors are extracted, and then A variety of machine learning classifiers are used to categorize the data. Additionally, this study uses Python 2.7.3 and the NLP methods module, NLTK.[1]

The results of this study indicate that using sunsets can improve performance by 3% to 6%. According to the author, future research of this kind might concentrate on cutting expenses and enhancing methods down to the paragraph level.[1]

Calvo et al. employ NLP to develop a common language that integrates mental health, HCI, and NLP to offer psychological support. According to the author, NLP can be used to create AI applications, create mental health applications, and create marketing apps based on user feedback and emotions. In this study, models based on data, labels, and interventions have been put forth. They used NLP to examine the data and interventions. The author has examined how NLP can be used to construct mental health apps from different kinds of data.[2]

In order to identify depression, Katchapakirin et al. looked at social media posts made by Thai people. Research has examined depression identification methods using natural language processing. This study was conducted using the TMHQ psychological health survey and microblogging platforms. To optimize classifications, SVM with Weak and random forest approaches with quick miners have been applied. Data with positive and negative polarity are divided into two groups. According to this survey, those who communicate negative viewpoints in private with me alone are significantly more depressed than those who share opinions with everyone and all day long. [3]

Using natural language processing (NLP), Nigam et al. exhibited the taxonomy of several sentiment analysis approaches and proved that logistic regression is more accurate than other methods. This study makes use of supervised machine learning and Twitter data. Among other things, the suggested method purges data of HTML decoding, URLs, and symbols. Next, consider phrases in both positive and negative situations. It shows statements in both positive and bad scenarios, but without the stop words this time. After characteristics are retrieved, data is classified and analyzed using different machine learning techniques.[4]

Mental health concerns are becoming increasingly important. The National Health and Morbidity Survey 2017 found that one in five people experiences depression, two in five experience anxiety, and one in ten experience stress. Higher education students bear the danger of joining the affected community. This project will use machine learning algorithms to classify students based on how stressed, depressed, and anxious they are. The information was given by students at a Kuala Terengganu higher education institution. [5]

This study assessed both individual depression symptoms and sociodemographic characteristics to ascertain if and where teens with depression sought out mental health therapies. Teens with major depression symptoms who sought therapy of any kind made up 53.38 percent of the sample.[6]

Sub-analyses of women without a history of depression were conducted. The characteristics that put women at the most risk for PPD were hardiness and psychological features, along with prenatal depression and anxiety. These traits should be considered for future clinical models that are implemented immediately after delivery in order to help identify women who are at high risk for postpartum depression and to provide individualized and affordable follow-up.[7]

The rise in psychological issues and the demand for high-quality healthcare have recently sparked research on the application of machine learning to mental health issues. We collect research and articles on machine learning techniques for predicting mental health problems by searching credible databases. Next, we group the research articles that we have gathered into groups according to mental health conditions, such as schizophrenia, bipolar disorder, anxiety and depression, PTSD, and problems related to the mental health of children.[8]

We concluded that the most significant predictors of mental health decline are the healthcare role held by frontline workers, recent sleep patterns, age, the amount of COVID-19-related news they typically consume daily, and their use

of alcohol and cannabis. These conclusions were reached after interpreting the various models used to analyze the data from the mental health survey.[9]

A mental illness is one of the disorders for which there is now no effective treatment. The most difficult task is figuring out if someone actually suffers from a mental illness. A person may be experiencing a specific situation for a variety of reasons, such as family, work-related stress, society, etc. Our investigation of this conundrum will be limited to predicting physical ailments in individuals and ascertaining the patient's state of being through the use of the pre-classified information. Moreover, the results of this application's tests can be used to demonstrate IoT in healthcare in a practical setting.[10]

**METHODOLOGY**

The proposed method's sequence diagram is shown in Fig. 1. We are going to use our dataset to first look for the null value. We cleanse the data if a null value is present. If there are any duplicate entries in our dataset, remove them and reindex the information. Next, we assigned labels to our dataset. We assign a number between 0 and 1 to our dataset simply because it is textual data. A 0 denotes normal health status, while a 1 denotes an unstable stage (such as depression, bipolar disorder, stress, panic attack, or anxiety). Next, we conduct a sentiment analysis of the dataset's positive and negative sentiments. Our textual dataset, which is displayed in fig. 2, was preprocessed. Initially, in the preprocessing step, we utilize the function After that, use lemmatization to clean up the texts and get rid of the stop words. We extract the true meaning of words using tokenization and stemming. Thus, the dataset will now be divided. With 30% designated as a test set and the remaining portion as a training set. Using these training data, all supervised classification techniques will be trained. After the model parameters have been trained, we will use them to forecast, providing prediction output for test data and comparing those classifiers. We will then use the classifier with the best accuracy on test data for the final evaluation.

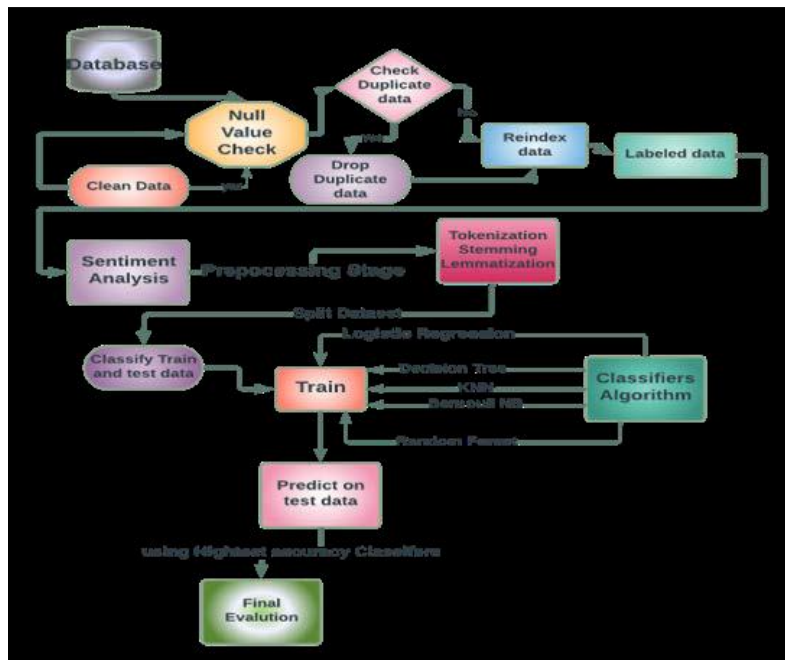


Fig. 1. Methodology.

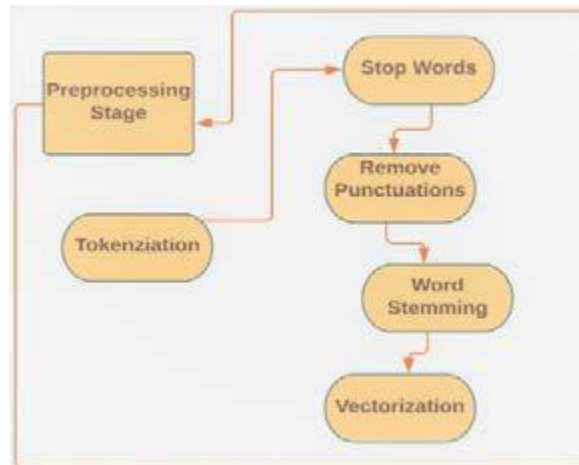


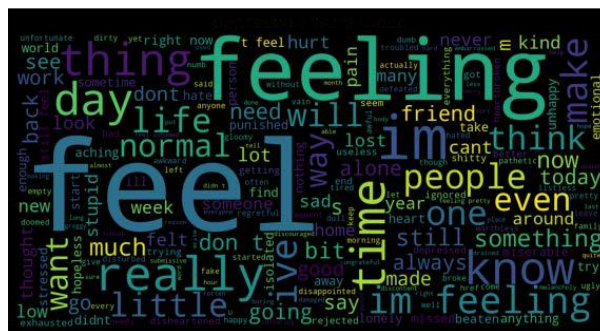
Fig. 2. Preprocessing step.

### A. Acquiring Information

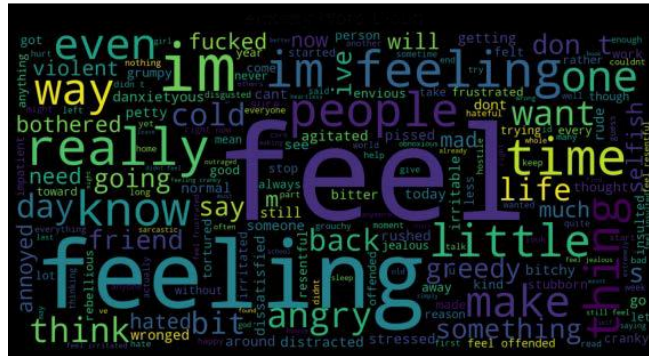
Our entire spectrum of intellectual, cognitive, and social well-being is included in mental health. It affects our judgment, social interactions, mental health, and ideas, feelings, and behaviors. Mental health is vital at every stage of life, from infancy to maturity. Therefore, we used an emotion-based data set from Kaggle [11] for the data set. After studying this dataset, we redesigned it for binary classification, designating 1 for the normal condition and 0 for the unstable states of anxiety, depression, panic disorder, stress, and bipolar disorder. After removing duplicate data, our dataset—which included 16,000 texts—contains 15893 characteristics.

### B. Information Evaluation

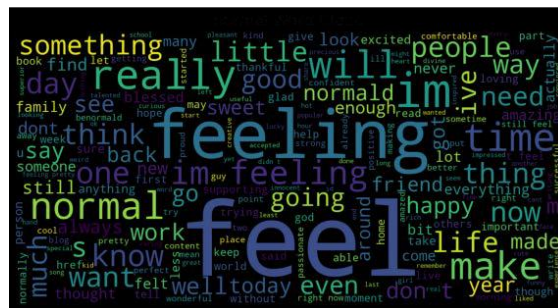
A potent tool for both understanding and imparting knowledge is data visualization. Sentiment analysis data can be shown using a wide range of techniques, including matrices, graphs, and histograms. Among the most used are word clouds, interactive maps, and other techniques. Here, Fig. 3 displays the dataset's word cloud, providing a preview of the entire collection of data. Here, it stands for anxiety, depression, and the normal state, respectively. The distribution of the entire dataset's mental health condition is shown in Fig. 4. Anxiety, despair, and panic disorder are all shown in our work as class 1 unstable states.



(a)



(b)



(c)

Figure 3: (a) Normal Word Cloud; (b) Anxiety; (c) Depression.

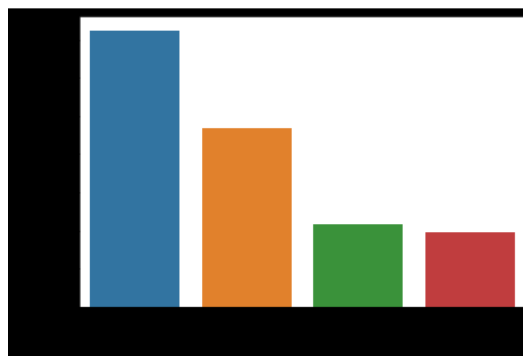


Figure 4: Mental Health States Distributed

**MODEL DETAILS**

In our suggested methodology, we employed the following five classifier algorithms: Random Forest, K-Nearest Neighbor classifier, Bernoulli Naive Bayes, Decision Tree, and Logistic Regression.

**A. NLP, or natural language processing**

The results of text mining are fed into natural language processing (NLP), one of the most advanced artificial intelligence techniques. NLP is the capacity for verbal communication in people. It is a method for turning spoken or written natural language inputs into outcomes that may be used. NLP requires interaction between a machine and a human, making it an interesting challenge to do. The study and comprehension of the interaction between computers and human language is the focus of the field of natural language processing, or NLP. These tools can be used by

developers to make practical tech applications. Numerous topics of interest have surfaced in NLP. Therefore, mining identified individuals, retrieving knowledge through documents, reading text messages across languages, synthesizing manuscripts, utilizing technological advancements to infer responses, and sorting & aggregating papers are the most crucial responsibilities in the main regions. In an academic atmosphere, theoretical concepts are regularly debated. NLP is a branch of data science that uses statistics and dynamic mathematical computations.[12]

### **B. Managed Algorithms**

A set of characteristics (independent variables) is used as a basis for supervised machine learning algorithms to predict a dependent variable. Using labeled datasets connected to predict the results of new, unlabeled experiment datasets, they ascertain the relationship between qualities and outcomes. They achieve this through gradual modification. The show was really well done. After that, a second dataset is usually used to test the algorithm's ability to predict known outcomes based on the attributes associated with them. Supervised machine learning algorithms can be broadly classified into two types. Algorithms come in two varieties: those for classification and regression. Classification algorithms, sometimes called classifiers, are expected to have authorized licensed use restricted to: Technology Institute of India (IIT) Mandi.

### **C. The Logistic Regression**

Logistic regression (LR) is one of the most widely used machine learning algorithms in the field of supervised learning. Predetermined independent factors are used to predict the classified explanatory variables. This logistic function has a value between 0 and 1.[14]

### **D. Bayes Bernoulli Navie**

Naive Bayes is the name of one variant of the Naive Bayes algorithm used in machine learning. It is particularly useful when the dataset has a binary distribution and the output label is either present or absent. The main advantage of this technique is that it simply detects features as binary values, like False or True, Ham or Spam. 0 or 1, No or Yes.[15]

### **E. K. The closest neighbor**

To determine the probability that a given data point belongs to one of two categories, the k-nearest neighbors (KNN) method uses the data points that are closest to the provided data point. Regression and classification problems can be tackled with k-nearest neighbor. Generally speaking, though, it is utilized in situations involving classification issues. [16]

$$(XX1,2)=\pi\Sigma(xx1ii-xx2ii)2nfi=1(1)$$

### **F. Random Forest**

Random Forest (RF), a well-known class of rules, employs the supervised studying paradigm. It can be used for machine learning tasks including regression and classification. It is based on supervised approaches, a tactic for combining various classifiers to solve a difficult issue and enhance the model's performance.[17]



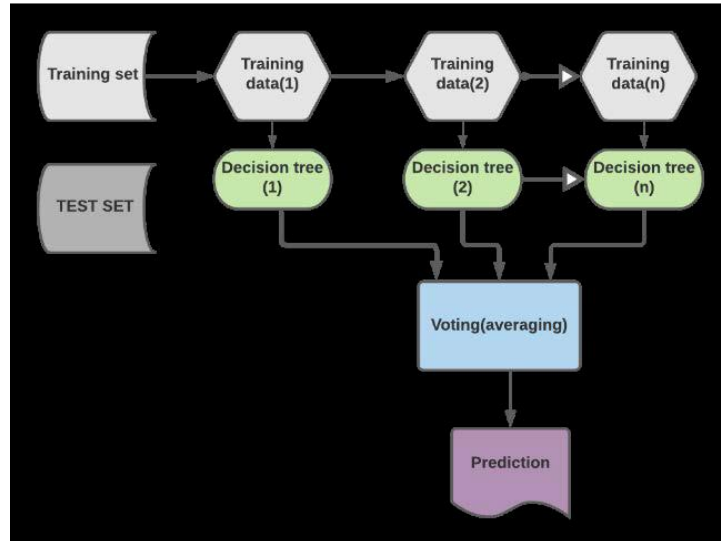


Figure 5: Random Forest Block Diagram.

**G. Decisions Tree**

The decision tree (DT) is most often used to solve classification problems, while it can also be used to solve machine learning difficulties. It is a tree-structured extractor, where the outcome is represented by a node in the tree and the prediction model is shown by pathways. Core nodes describe the features of the dataset.[18]

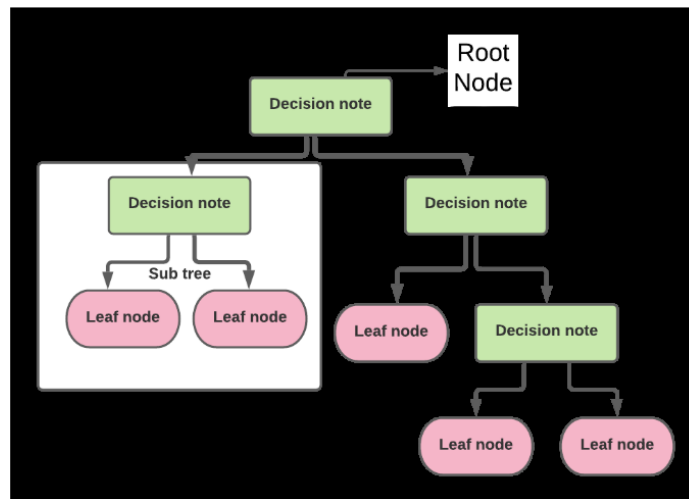


Fig. 6. Decision Tree Block Diagram

**ANALYSIS OF THE RESULT**

K-fold, or K=5) Every experiment employs cross-validation to assess the effectiveness of the suggested methodology. Performance is measured using three factors: efficiency, reliability, and accuracy. F-measure, recall, and precision are used in every experiment [19].

**A. Assessments**

Positive numbers that are correctly predicted and show that the actual and forecast class values are both yes are known as True Positives (TP). For example, if the predicted class implies that the person is also mentally ill and the definite

value indicates that the person has a mental illness. True Negatives (TN) are negative values that indicate that both the projected class value and the true class are false and have been accurately anticipated. For instance, we can presume that the anticipated class is the same if the actual result shows that the individual's mental health is not okay. A False-positive [FP] occurs when the real class is no, while the expected class is yes. For instance, the predicted value suggests that the person is not mentally well even though the individual is. When the actual class appears but not the anticipated one, this is known as a False Negative (FN). In contrast to the expected class value, which suggests that the person is mentally unstable, the genuine class value, if it is apparent, indicates that the person is in excellent health. Once we comprehend those four attributes, we can calculate F1 score, Accuracy, Precision, and Recall. [19].

Accuracy is the statistic most commonly used to evaluate an algorithm's performance in classification tasks and is, in many cases, the first choice. The ratio of correctly predicted data items to total observations is commonly known as the appropriate data item to witness proportion. [19]

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

"The quantity of significant data bits from among a group of data items" is the definition of precision. Stated differently, what proportion of the strongly predicted observations made by an algorithm are positive? [19]

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

In recall, the number of significant data items that have been identified is displayed. [19]

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

when calculating an algorithm's performance, the f-score incorporates both precision and recall[19]

$$F1\ Score = \frac{2 * (Recall * Precision)}{Recall + Precision}$$

## B. Error estimation

The mean squared error is commonly used to assess how closely a collection of data resembles a linear regression. The lengths between series of data and the regression model are squared in order to achieve this. These lengths are the "imperfections". To eliminate unwanted signals and highlight important differences further, the final squaring is necessary. Since you are examining the total of a number of errors, it is known as the mean squared error.[19]

The lower the MSE score can be, the better. Achieving a very minimal mean squared error could be challenging. As the MSE accounts for both the bias and dispersion of the estimator, it is frequently referred to as the following stage (from the premise) of the cost function. MSE defines the range of an unbiased estimator. Since variance prediction is similarly equivalent to the squares from the under parameter, MSE also makes use of the same measurement scheme.[19]

$$MSE = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2$$

The gap between the observed and expected data, or how well the data fit the supplied, is expressed by the Root Mean Squared Error. The answer variable indicates that this is typically in the same unit. The more closely the projected data resembles the real data, the lower the RMSE. [19]



$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_{obs,i} - x_{model,i})^2}{n}}$$

R2 is a statistic that assesses the potential uniqueness of many variations in one variable at several in another. R-squared is a straightforward metric that ranges from 0, which indicates that the suggested method does not improve forecasting over the mean hypothesis, to 1, which indicates complete accuracy. The R-squared of the regression model is rising proportionately, indicating that it is rising.[19]

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

**C. Classifiers' Performance Analysis**

Table 1 displays the classification results for the confusion matrix's True Positive (TP), False Positive (FP), False Negative (FN), and True Negative entries. (TN). We calculated the f1-score, recall, and precision for the data in Table II. Table II indicates that while the accuracy value is higher in the mentally stable state (LR), the best precision value is shown in the mentally ill state (Class 1) by the RF. Then, BernoulliNB (NB), RF, DT, and KNN have the highest values for the mentally stable condition. Following RF and LR, DT, NB, and KNN exhibit a high precision value in the (class=1) mentally unwell state. In order to solve that conundrum, we examine the F1 score. Given that the F1 score demonstrates a harmony between precision and memory. A good f1-core, which indicates accurate detection, is implied by low false positives and false negatives. Table 2 shows us that the f1 score After NB, RF, DT, and KNN, who perform the lowest in both states—NB, RF, DT, and KNN in a mentally ill state—LR is the best performer in both. However, both states have high LR F1 Scores. LR outperforms other classifiers with an F1 score of 0.94. Table 2 demonstrates that the accuracy of Logistic Regression is higher than that of the other four classifiers. Thus, the best performer in this case is logistic regression.

Table I: CONFUSION MATRIX'S TRUE POSITIVE (TP), FALSE POSITIVE (FP), FALSE Negative (FN), AND TRUE NEGATIVE (TN)

Classifiers	TP	FP	FN	TN
LR	2474	160	130	2031
RF	2098	93	452	2098
NB	2440	253	158	1938
KNN	2149	573	455	1618
DT	2097	164	507	2027

Table II: Performance Evaluation Metrics (Accuracy, Precision, Recall, F1-Score, Precision)

Classifier	precision	recall	f1-score	Accuracy
LR	0.93	0.95	0.94	0.93
RF	0.95	0.82	0.88	0.88
NB	0.90	0.93	0.92	0.91
KNN	0.78	0.82	0.80	0.78
DT	0.92	0.80	0.86	0.86

The error analysis has been displayed (r2-score), and it contains meaning squared error (MSE), root mean square error (RMSE), and r-squared error. The classifier is better when the MSE and RMSE values are lower. Table 2 demonstrates

that the accuracy of Logistic Regression is higher than that of the other four classifiers. Thus, the best performer in this case is logistic regression. In order to categorize, the training model in Figure 7 is logistic regression.

Table III: Test and Training Data Error Evaluation Metrics (MSE, RMSE, AND R2-SCORE)

Classifier	Train Data			Test Data		
	MSE	RMSE	R2	MSE	RMSE	R2
LR	0.025116	0.15848	0.8985	0.060479	0.24593	0.75627
RF	0.000983	0.031356	0.99603	0.116579	0.34144	0.5302
NB	0.050947	0.22572	0.79412	0.085714	0.29277	0.65458
KNN	0.116821	0.34179	0.52791	0.214389	0.46302	0.13603
DT	0.000983	0.031356	0.99603	0.146611	0.38297	0.40917

```

> text=['life is so unfair' ]
test_result = lr_clf.predict(vectorizer.transform(text))
print(test_result)

[1]

> text=['I am good' ]
test_result = lr_clf.predict(vectorizer.transform(text))
print(test_result)

[0]

```

Figure 7 shows an example depiction of the optimal training model for evaluation.

## CONCLUSION

We give a detailed comparison of the five Classifier Algorithms discussed above in our paper. According to the findings of the experiments, Logistic Regression has the highest performance, whereas others specialize in certain scenarios. In the future, we will work with other social site data and other classifier algorithms can also be considered.

## REFERENCES

1. M. Kanakaraj, and R M. R Guddeti, "NLP based sentiment analysis on Twitter data using ensemble classifiers". In 2015 3rd international conference on signal processing, communication, and networking (ICSCN) (pp. 1-5). IEEE 2015, March
2. N. Glozier, 2017. Effectiveness of eHealth interventions for reducing mental health conditions in employees: A systematic review and metanalysis. The Technical Writer's Handbook. Mill Valley, CA: University Science, PloS one, 12(12), p.e0189904M. Young, 1989.
3. K. Katchapakirin, K. Wongpatikaseree, P. Yomaboot, and Y. Kaewpitakkun, "Facebook social media for depression detection in the Thai community". In 2018 15th International Joint Conference on Computer Science and Software Engineering (JCSSE) (pp. 1-6). 2018, July IEEE.

4. S. Nigam, A. K. Das, and R. Chandra, "Machine Learning Based Approach to Sentiment Analysis." Proceedings - IEEE 2018 International Conference on Advances in Computing, Communication Control and Networking, ICACCCN 2018, 157–161, 2018.
5. S. Mutalib, "Mental health prediction models using machine learning in higher education institution". Turkish Journal of Computer and Mathematics Education , 12(5), pp.1782-1792,2021
6. M. L. Dobias, M. B. Sugarman, M C. Mullarkey, and J. L. Schleider, "Predicting mental health treatment access among adolescents with elevated depressive symptoms: Machine learning approaches". Administration and Policy in Mental Health and Mental Health Services Research, 49(1), pp.88-103,2022.
7. S. Andersson, D. R. Bathula, S. I. Iliadis, M. Walter, and A. Skalkidou, "Predicting women with depressive symptoms postpartum with machine learning methods." Scientific reports, 11(1), pp.1-15,2021.
8. J.Chung, and J.Teo," Mental Health Prediction Using Machine Learning: Taxonomy, Applications, and Challenges." Applied Computational Intelligence and Soft Computing, 2022.
9. M. Rezapour, and L. Hansen," A machine learning analysis of COVID-19 mental health data". Scientific reports, 12(1), pp.1-16,2022
10. P. Kumar, R. Chauhan, T. Stephan, A. Shankar, and S. Thakur, "Machine Learning Implementation for Mental Health Care Application: Smart Watch for Depression Detection." In 2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence) (pp. 568-574). IEEE,2021
11. Emotion Classification | Kaggle."[online]. Available: <https://www.kaggle.com/datasets/praveengovi/emotions-dataset-for-nlp?> [Accessed: 04-16-2020].
12. D. H. Maulud, S. R. Zeebaree, K. Jacksi, M. A M. Sadeeq, and K. H. Sharif, "State of art for semantic analysis of natural language processing". Qubahan Academic Journal, 1(2), pp.21-28,2021.
13. C. J. Harrison, and C. J. Sidey-Gibbons," Machine learning in medicine: a practical introduction to natural language processing". BMC Medical Research Methodology, 21(1), pp.1-11,2021.
14. J. Han, M. Kamber, and D. Mining, "Concepts and techniques". Morgan Kaufmann, 340, pp.94104-3205,2006.
15. A. Kharwal. "Bernoulli Naive Bayes in Machine Learning | Aman Kharwal." Bernoulli Naive Bayes in Machine Learning. Jul. 27, 2017. <https://thecleverprogrammer.com/2021/07/27/bernoulli-naive-bayes-in-machine-learning/> (accessed: Nov. 14, 2022).
16. H. Elmunsyah, R Mu'awanah, T. Widiyaningtyas, I. A. Zaeni, and F.A. Dwiyanto," Classification of employee mental health disorder treatment with k-nearest neighbor algorithm". In 2019 International Conference on Electrical, Electronics and Information Engineering (ICEEIE) (Vol. 6, pp. 211-215). IEEE, 2019, October
17. M. Z. Islam, J. Liu, J. Li, LL. Liu, and W. Kang, "A semantics aware random forest for text classification". In Proceedings of the 28th ACM International Conference on Information and Knowledge Management (pp. 1061-1070), 2019.
18. B. Charbuty, and A. Abdulazeez, "Classification based on decision tree algorithm for machine learning". Journal of Applied Science and Technology Trends, 2(01), pp.20-28, 2021.
19. M. A. Haque, I. J. Dristy, and M. G. R. Alam, "Symptomatic & Non-Symptomatic Hepatocellular Carcinoma Prediction using Machine Learning." In 2021 International Conference on Electrical, Computer, Communications, & Mechatronics Engineering (ICECCME) (pp. 1-6). IEEE, 2021.