Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606

ICASET
2024

Research Article
Collection: Intelligent Computing of Applied Sciences and Emerging Trends

A Comparative study: Mental Patient Disorder Classification Using Text Mining

Mutiullah Jamil[1*], Ayesha Qureshi[2], Muhammad Waleed[1], Abhia Ejaz[2], Shakeel[1], Abdul Haseeb Wajid[2], and Aqeel Ur Rehman[1]

[1]Khwaja Fareed University of Engineering and Information Technology, Rahim Yar Kahn, Pakistan.
[2]Department of Information Technology, Islamia University of Bahawalpur, Bahawalpur Punjab, Pakistan.
[*]Corresponding Author: Mutiullah Jamil. Email: mutiullah@kfueit.edu.pk

Academic Editor: Salman Qadri **Published:** April 01, 2024

Abstract: A key element of community well-being is mental health, which is influenced by social and organizational contexts in which people live and work in addition to personality traits. In spite of research on the mental health conditions of specific populations, there hasn't been much effort to concentrate on developing strategies for identifying and assessing the effects of mental health problems. In this article, we will use supervised machine learning algorithms to detect mental health. The data set we use is from Kaggle. We employed logistic regression, K nearest neighbor, and random forest, among other supervised machine learning techniques. To find the best performance, we compare and evaluate model results.

Keywords: Machine learning; Mental Health; TF-IDF; Multi classifier.

1. Introduction

Mental health is rapidly becoming one of the world's most popular problems of public health. On social media sites where people are able to convey their emotions, feelings and ideas, machine learning techniques are quickly used. Online social networks have gained popularity in the past few years as a way for users to share user-generated or user-curated material, such as posting updates about themselves, photos, and current locations Additionally, users can interact with one another by leaving comments and striking up discussions regarding one another. Users can express their feelings and ideas and report on their everyday activities in these discussions [1] which provides a number of useful data about their social behavior [2]. For instance, Twitter has over 310 million active accounts and Facebook has over 1.7 billion active monthly users [3]. Both platforms generate enormous volumes of data that, with certain restrictions, can be mined to find significant patterns in user behavior. Data science has been established because of the ever-increasing volume of data and the analysis and computer power it needs to be addressed. For this new situation, machine learning approaches which let researchers to extract knowledge from massive data sets have been repurposed and used to evaluate data and construct predictive models in a number of fields, including finance [4] economics [5] politics [6] and criminal justice [7][8].

Researchers have been able to search enormous health-care databases for patterns and important information using data science methods in medical research [9]. A subgroup of this study looked at using status updates from social networking websites to analyze symptoms of mental illnesses [10]. Based on the signs and symptoms of mental disorders, text mining and machine learning can be utilized to create automatic detection systems for mental health problems. Technologies like as text mining, social network analysis, and image analysis are presently available to find odd behavior and communication patterns on social media platforms. [11]. Computer science includes machine learning as a subset. Machine learning is concerned with the development of computer programs that can evolve and change when they are exposed to new, previously unknown data. A type of testing entails predicting and statistical research. There are two primary layers of machine learning. There are two types of learning: unsupervised and supervised, and in this post, we will focus on the supervised learning phase, which is the process of gathering work from labelled findings. The training database contains training examples. In the supervised study, each training sample contains the completely input value as well as the relevant output value. Separation and rearrangement can be used as the foundation for supervised learning. A split is when the output value is split into groups, while a regression is when the output value is a true value. Classification is a supervised approach for learning to classify new examples based on information gathered from a set of previously classified training cases. Clustering is the corresponding unsupervised approach. It divides incoming data into classes using an intrinsic similarity metric. General pattern recognition issues include clustering and classification, which gives a given input value to a specific output value [11] [12].

2. Related Work

While numerous studies relating to mental health and other data may not meet our inclusion requirements, they provide useful information on trends in study in this field. In previous research, mental health problems or suicide risk were predicted by different data sources such as clinical notes [12] speech analysis [13] facial [14] and multimodal analysis [15]. Additional research was excluded as social media data was used to predict various results, such as Hanson et al, who used Twitter data in order to predict the use of drugs [16]. In addition, new investigations have examined why Twitter users write about their mental health [17]. Depression research is much older than the Internet Numerous reputable scales and standards have been created using user research or questionnaire surveys as their foundation. Beck's Depression Inventory [18] for example, consists of 21 questions about the mental and physiological status of the user.

Another research study is the CES-D Scale [19] which includes 20 items about mental health conditions such as users' guilt feelings and sleeping habits. The questions either feature multiple answers with varying scores or ask users to rate the severity of their circumstance.

The severity of depression is determined using a total score scale. As a fundamental need for diagnosing depression, the Diagnostic and Statistical Manual of Mental Disorders (DSM) [20] presents nine categories of depressed signs, including low mood and diminished interest. Clinicians often check to see if these symptoms have developed over time before drawing a conclusion. Over many years, these standards have been extensively verified and used in actual situations. These criteria, however, might not have been updated as extensively as they could have been, and they might not have included all new behaviors and symptoms, including those communicated by contemporary social media, because it took the DSM 12 years to evolve from DSM-IV to DSM-V.

Many academics use data from social media platforms for a variety of online health, medical, and psychosocial studies [21]. When assessing generalizability, it is crucial to take the target population's online content into account. [22] [23] conducted a thorough meta-analysis of the efficacy of mental health therapy at work and discovered that depression is the most prevalent mental illness component in the majority of developed countries. The scientifically helpful measures can be used to prevent common mental health, [24].

The author of this paper [25] offered guidelines for projecting anxiety based on such things as the working environment of a person (home or office) and some additional personal characteristics. This is a hybrid model combining logistic regression and decision trees to improve accuracy.

A smartphone-based sensor system was utilized by the author of [26] to track changes in the condition of bipolar patients. Provide a percentage recall and precision early warning system. A multimodal stress detection and wearable headband monitoring was proposed by the author [27].

The author of [28] predicted generalized anxiety disorders among women and declared that women are around twice as likely as males to receive GAD (generalized anxiety disorder). The author of [29] used wearable sensors to predict bipolar disorder based on heart rate variability.

The author of [30] employed machine learning techniques to detect stress in workers and discovered factors that lead to mental stress. With 75.13 % precision and accuracy, random forest was found to be the best option.

The author of [31] used HRV to identify stress and several machine learning techniques to predict stress. The author [32] employed heartbeat data to identify stress and ML classification algorithms; data are gathered at intervals of 5 minutes such that after 5 minutes of heartbeat information are collected, the user receives a 5-minute relaxation interval. Studying the effects of social resources, coping mechanisms, and stress on individuals receiving treatment for depression, Billings and Moos [33].

Neils Rosenquist, Fowler, and Christakis [34] found that depression levels shown diffusion up to three degrees of separation in a large social network, suggesting that depression has a network influence component Kawachi et al. looked into the role that social capital and relationships have in maintaining psychological well-being and treating behavioral health issues in [35].

Prior studies have demonstrated that people's social environments offer crucial information for comprehending and addressing mental health issues. In the discipline of psycholinguistics, Oxman et al. [36] demonstrated that linguistic analysis of speech can be used to categorize individuals into diagnostic groups, such as those experiencing paranoia and sadness. It's also been shown that computerized text analysis can reveal clues concerning neurotic tendencies and psychiatric disorders [37].

In recent years, there has been a lot of interest in using internet data to predict and analyses public health behaviors. Google Flu Trends1 uses online search queries to provide detailed forecasts about flu infections. Paul and Dredze [38] developed a disease-specific topic model based on Twitter tweets to simulate behavior around a variety of diseases that are significant in public health. Collier et al. [39] discovered evidence of a high association between social media signals and diagnostic influenza case data through language modelling of Twitter posts. Based on geotagged tweets, Sadelik et al. [40] created statistical models that predicted the spread of infectious disease (e.g. flu) among individuals (also see [41].

Although a wide range of public health issues have been studied in this body of work, research into the use of social media to better understand behavioral health diseases is still in its infancy. According to Park et al. [42], people do share on Twitter about their depression and even their depression therapy.

In a different study [43], we examined language and emotional correlates for the postnatal course of new mothers. We subsequently developed a model to forecast severe behavioral changes in new mothers. Therefore, it appears from this early research that social media can be employed as a signal in depression research. The present study looks at general depression at the community level, which broadens the focus of social media-based depression research.

People can freely share their opinion online due to today's social media technologies, resulting in a wealth of rich and essential content that can lead to new discoveries or provide more information [44]. As a result, an increasing number of academics use data on social media to carry out several online medical, psychosocial and health studies [45]. However, when considering generalizability, it is necessary to thoroughly examine the target demographic's online material [46]. Additionally, a two-phase questionnaire known as the "Indicator Tool" was established to gather data on employee perceptions of working conditions. They underlined the HSE's objective of creating a framework that will enable companies to manage work-related stress in an efficient manner and, consequently, lower the frequency and occurrence of this type of stress. Stress at work has numerous detrimental repercussions on one's physical, mental, and organizational well-being [47]. This research also shown how workers are responsible for developing strategies and systems to lessen the detrimental impacts of job stress. These results imply that there is a pressing need for computer-based methods of diagnosing and evaluating mental health issues.

Although numerous of these studies have examined the problems of mental health at work, none of them focused on mental stress in IT environments, nor on creating a solution design understanding, such as utilizing data-driven methods to detect mental stress. This study investigates numerous features of tech employees and uses machine-learning techniques to assess their mental health difficulties. Several studies [48] have shown that categorization can be increased by extracting features such as information about the pitch of the voice from recorded speech data. Software has been created for extraction such data such as the py Audio Analysis tool [49]. You may also see how often and how long telephone conversations are used for an idea of the patient's social activity.

3. Materials and Methods

This section goes over the proposed approach in detail, including the dataset utilized in the experiment, feature extraction techniques, selected machine-learning classifiers, and the accuracy measures to evaluate performance. The goal of the methodology is to use various classifiers to find the best classifier that performs well on mental patients Disorder. SVM, RF, and KNN are three machine-learning algorithms that are used to generate learning models, as well as feature extraction approaches. The Python-based Scikit-learn tool kit is used to implement many of these methods. The dataset we are using contains a large number of parameters that have an impact on Mental Patients with Disorders. The influencing elements were divided into two categories: input variables and output variables, with the output variable representing the label depending on the input. I will utilize a variety of classifiers, such as RF, SVM, and KNN, as well as some pre-processing techniques, such as TF-IDF and BOW, and evaluation parameters, such as Accuracy, Precision, Recall, and F1-Score, to measure whether or not the person has a mental disorder. To improve model accuracy, we first collect data on mental disorders and then use preprocessing techniques such as Remove Missing Values, Remove Numbers, Remove Special Characters, Remove Punctuation, Remove Stop Words, Convert to Lower Case, and Stemming. After that, I will use feature extraction techniques like TF/IDF and BOW to extract features before splitting the data into two subsets: training data (75%), and testing data (25%). To train the model, use a different classifier on the training data. After that, I will use evaluation parameters like Accuracy, Precision, Recall, and F1-Score to evaluate the performance of classifiers, then we will check the model's accuracy, and the classifier that gives us the most accuracy or accurate result will be chosen as our model, which was shown in Figure 1.

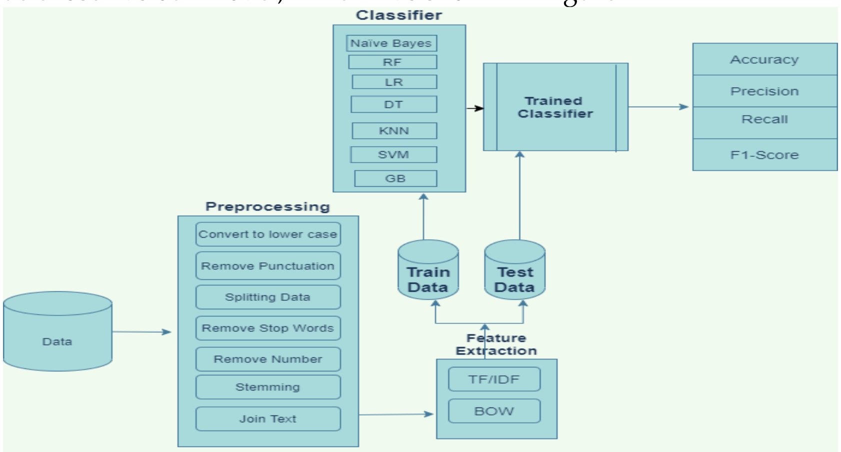

Figure 1. Proposed Methodology Diagram

3.1. Data Description

We took this data set from Kaggle; it is a train.csv file with 2833 rows and 116 columns; the columns we will be using are (Text, Label). Text data is our target label; we need to classify people's remarks into groups of 0 and 1. There are 2833 data points in the training set. Each data point has two specifications or features, as well as one target variable (labelled column). This dataset was used to train and evaluate a model based on preprocessing approaches and a variety of classifiers. This information was gathered from the Kaggle online community. To get the highest level of accuracy, different numbers of classifiers are used. The purpose of this study is to improve the accuracy with which people's reviews about patients are analyzed. , which was shown in Figure 2.

	subreddit	post_id	sentence_range	text	id	label	confidence	social_timestamp	social_karma	syntax_ari	...
0	ptsd	8601tu	(15, 20)	He said he had not felt that way before, sugge...	33181	1	0.8	1521614353	5	1.806818	...
1	assistance	8lbrx9	(0, 5)	Hey there r/assistance, Not sure if this is th...	2606	0	1.0	1527009817	4	9.429737	...
2	ptsd	9ch1zh	(15, 20)	My mom then hit me with the newspaper and it s...	38816	1	0.8	1535935605	2	7.769821	...
3	relationships	7rorpp	[5, 10]	until i met my new boyfriend, he is amazing, h...	239	1	0.6	1516429555	0	2.667798	...
4	survivorsofabuse	9p2gbc	[0, 5]	October is Domestic Violence Awareness Month a...	1421	1	0.8	1539809005	24	7.554238	...

Figure 2. Dataset

3.2. Data Loading

All of our data comes from social media sites in English. Reddit's Dreaddit and GoEmotions are based on the social media network Reddit, while Vent is based on the social media platform Vent. Dreaddit is made up of 3,553 named portions of posts from r/domesticviolence, r/survivorsofabuce, r/anxiety, r/stress, r/almosthomeless, r/assistance, r/food pantry, r/homeless, r/ptsd, and r/relationships, among others. Stress is labelled in 52.3 % of the data, whereas nonstress is labelled in 47.4 %.

3.3. Visualization of Data

Data display is the process of converting massive data sets into statistical and graphical representations. Data science and exploration approaches are crucial for making data more understandable and usable. For rapid knowledge absorption and improved understanding, visualization necessitates a large complicated amount of data to represent charts or graphs. , which was shown in Figure 3.

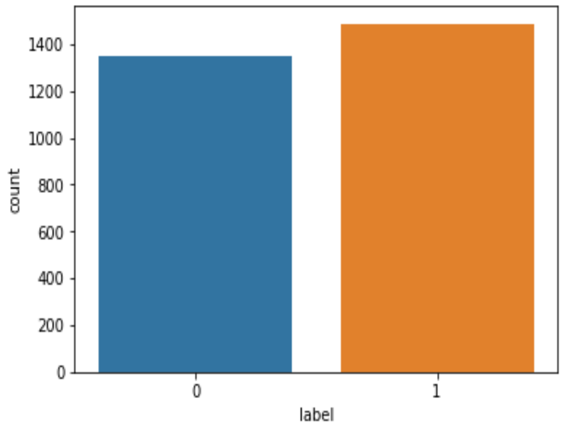

Figure 3. Visualization of Data

3.4. Pre-processing

We want to go over the pre-processing used by experiments to evaluate the performance of both the proposed strategy and the selected machine-learning classifiers before getting into the details of the suggested approach. The dataset frequently contains noise in the form of additional data that does not contribute to classification and must be erased. The process of reducing noisy and incomplete data is known as data pre-processing. The importance of preprocessing in improving classification accuracy cannot be overstated. The dataset in this study has a lot of useless information, which has no bearing on the prediction. Because the training and testing times rise as the dataset grows larger, deleting unneeded data can help speed up the training process. Preprocessing refers to steps performed to clean up the data to increase the model's learning efficiency. Python's natural language toolkit (NLTK) has been used for this purpose. It is a collection of text processing that may be utilized in a number of applications, and in our work, we employed NLTK 3.5b1 with Python. Figure 1 displays the pre-processing steps used in this investigation. The punctuation ([], () -, _, :, /, |, ;,...., “ and ') as well as Numbers such as 0, 1, 2, 3, 4, 5, 6, 7, 8, and 9 are then deleted from the reviews because they do not help to the text analysis. It makes it difficult for the model to distinguish between punctuation and other characters. Finally, stemming is carried out. The affixes from the words are removed in a crucial pre-processing step. It reduces long words to their simplest forms. For example, the modified variants of the word "love" include "loves," "loved," and "loving." Stemming transforms these words into their original/root form, which helps classifiers perform better.

3.5. Classifiers

3.5.1 Logistic Regression Model

When the goal variable is categorical, a classification procedure called logistic regression is applied. When the data has a binary output, such as 0 or 1, the Logistic Regression algorithm comes into picture. One of the most prominent algorithms in machine learning is logistic regression under the Supervised Learning approach. It is a way to predict a variable based on a number of independent variables. Logistic regression is extremely similar to linear regression, except for how they are used. The below image is showing the logistic function: , which was shown in Figure 4.

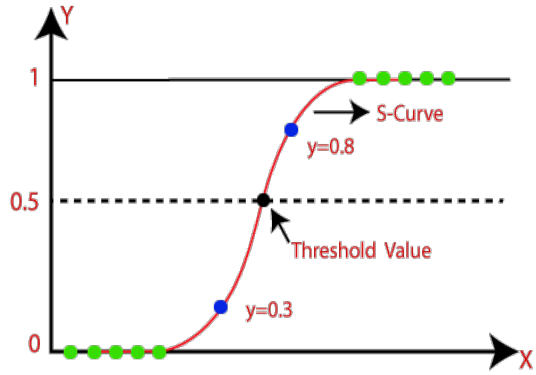

Figure 4. Logistic Regression Function

3.5.2. Decision Tree Model

A decision tree is an element of a classification algorithm in machine learning which includes solutions problems with regression utilizing the classification rule (from the root to the leaf node). It's structure is a flowchart, with a feature test (e.g. whether or not the random number is bigger than the number) and a regression problem in each leaf node. The decision tree field in machine learning in today's world is wide. The algorithm has two entities: the root and leaf nodes. For example: , which was shown in Figure 5.

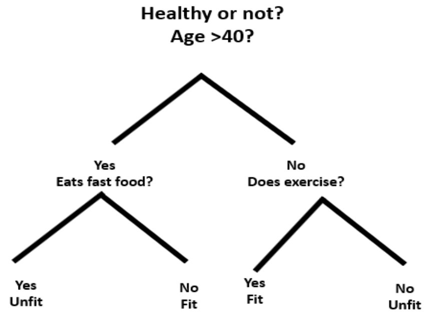

Figure 5. Working of Decision Tree

3.5.3. SVM Model

The Support Vector Machine approach for regression and classification models is a basic but powerful Supervised Machine Learning algorithm. The SVM approach can be applied to both linearly and non-linearly separable datasets. The support vector machine approach performs brilliantly even with tiny amounts of data. , which was shown in Figure 6.

Figure 6. Difference b/w linear and Non-linear data

3.5.4. Random Forest Model

Random Forest is an algorithm that uses the supervised approach of learning. It may be used for classification and regression problems in machine learning. It is a method of merging a number of classifiers to solve a complex problem and boost the performance of the model. The image below illustrates the Random Forest method: which was shown in Figure 7.

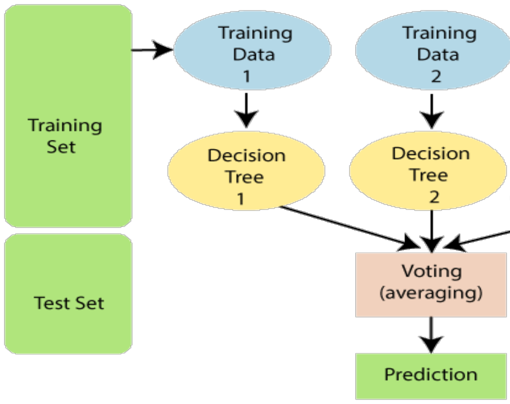

Figure 7. Working of Random Forest

Example: A dataset with various pictures of fruit is available. This data set is therefore provided to the Random Forest Classifier. A part of the dataset is given to work with each decision tree. The Random Forest Classifier Predict the ultimate choice based on most results, if a new data point comes in the process of the training phase. Take the illustration below. , which was shown in Figure 8.

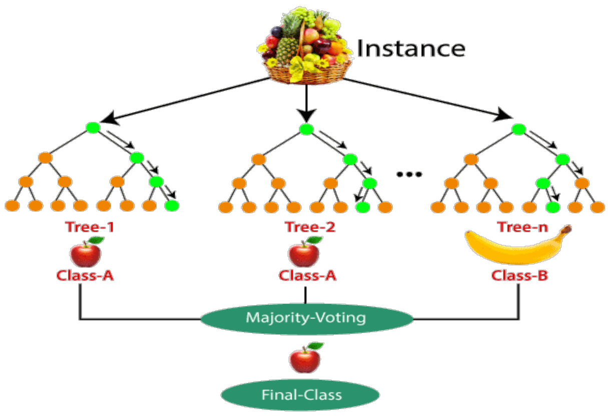

Figure 8. Random Forest Example

3.5.5. KNN Model

The KNN algorithm is a type of supervised machine-learning approach that can be used to tackle issues that predict classification and regression. However, it is largely used in industry to tackle problems of categorization and prediction. One of most important Machine-Learning algorithm is K-Nearest Neighbor algorithm and is based on supervised learning techniques. The new case/data cases are similar in the K-NN technique and allocate the new case to the most similar category of existing categories. , which was shown in Figure 9 and 10.

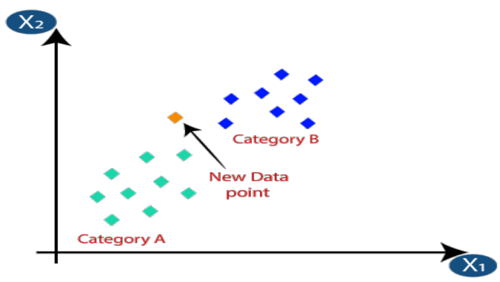

Figure 9. Working of KNN

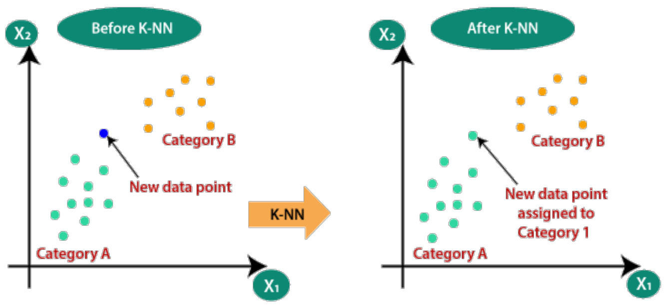

Figure 10. Identification of Data

3.6. Evaluation parameters

Different metrics that are used to measure performance of the model.

3.6.1. Confusion matrix

It is a 2*2 matrix that tells you about the model's performance, which was shown in Figure 11.

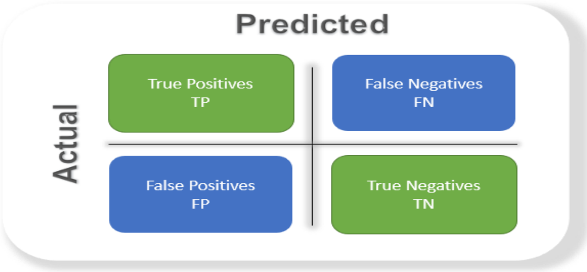

Figure 11. Confusion Matrix

3.6.2. Accuracy

The most popular metric for assessing a model is not a trustworthy measure of how well it performs, though. The situation gets worse when there is an imbalance in the classes.

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

3.6.3. Precision

Positive instances as a percentage of the overall positive instances predicted. The model prediction from the whole dataset is positive and denominates. Take it as an exercise "The model is just how correct it is when it says its right."

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

3.6.4. Recall

As a percentage of the total number of positive instances, positive instances. The total number of positives in the collection therefore represents the denominator (TP + FN). Suppose you are trying to find "how much more right the model was missing when it was showing the right ones."

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

3.6.5. F1 Score

Precision and recall have a harmonic mean. This factor considers both, so the greater the F1 score, the better. As you can see, if one goes low in the numerator, the ultimate F1 score drops down significantly. Therefore, if the positives predicted are indeed positives (accuracy) and the model does not miss positives and predicts them negative, it does well in the F1 score (recall).

$$\frac{2}{\frac{1}{precision} + \frac{1}{recall}} = \frac{2 * precision * recall}{precision + recall}$$

4. Results and Discussions

This section provides details on the research's experimental results along with a discussion of the findings. The initial stage of the classification process was testing these learning/classifying models' accuracy using text data functions. Examining the accuracy of various classification models, including GBM, SVM, RF, MNB, KNN, and DT, was the main goal. The outcomes were contrasted with extraction techniques like TF-IDF and BOW. To test the effectiveness of various classifier modules, P0, R0, F0, is precision, recall, and F1 - Score of patient comments (0) class; P1, R1, F1 - precision, recall, and F1 - Score comments of people regarding patients (1) class. According to the results of the studies, the LR classifier performs well when used with TF-IDF features. The results obtained from the TF-IDF feature are shown in Table 1 and Table 2 and, which was shown in Figure 12 and Figure 13.

Table 1. Accuracy of Classifier with TF-IDF

Classifier	Accuracy	Class(0)			Class(1)		
		P0	R0	F0	P1	R1	F1
DT	0.64	0.62	0.52	0.57	0.61	0.70	0.65
GBM	0.64	0.63	0.61	0.62	0.65	0.67	0.66
MNB	0.70	0.83	0.49	0.62	0.66	0.91	0.76
SVM	0.73	0.72	0.71	0.72	0.74	0.75	0.74
KNN	0.67	0.77	0.45	0.57	0.63	0.87	0.74
RF	0.69	0.73	0.59	0.65	0.68	0.79	0.73
LR	0.74	0.75	0.71	0.73	0.75	0.78	0.76

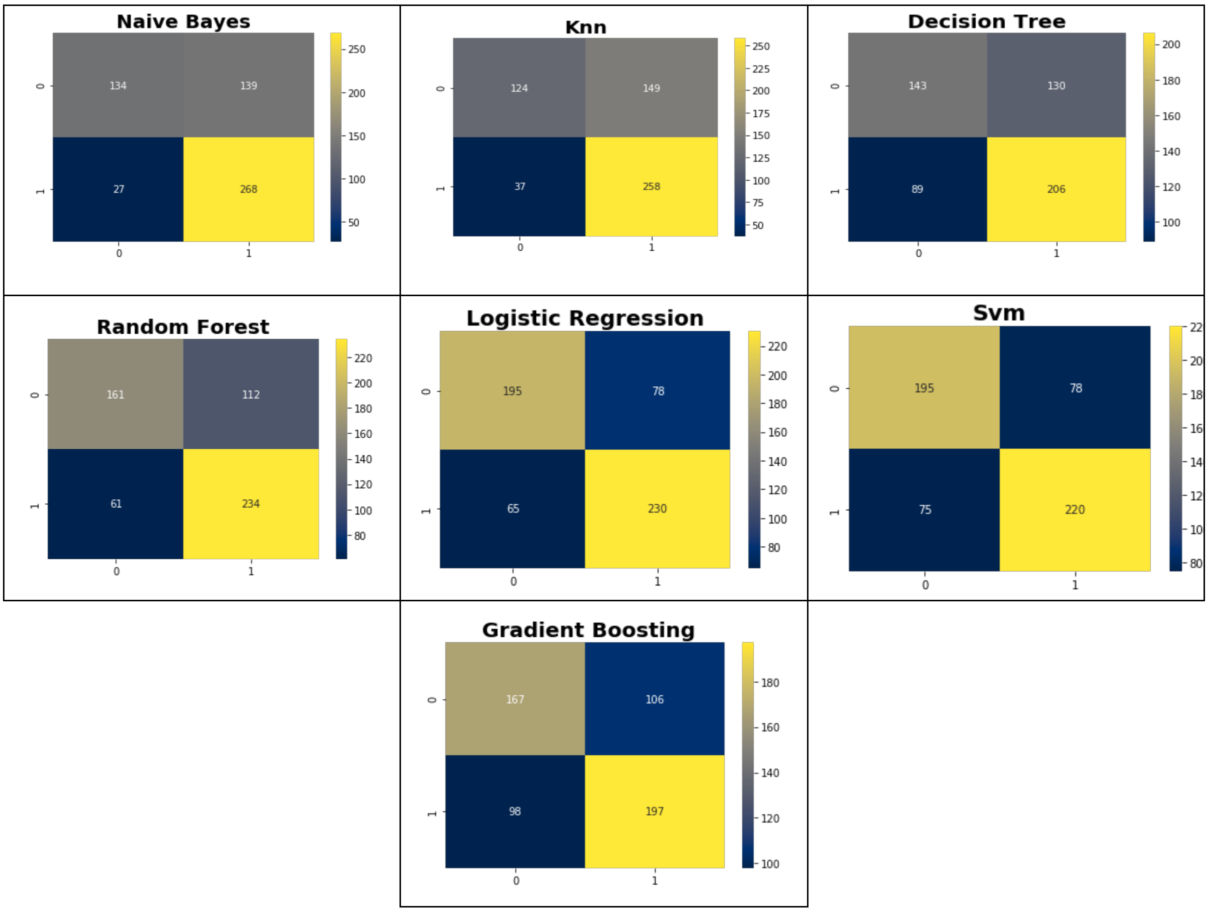

Figure 12. Confusion Matrix with TF-IDF Feature

Table 2. Accuracy of Classifier with BOW

Classifier	Accuracy	Class(0)			Class(1)		
		P0	R0	F0	P1	R1	F1
DT	0.68	0.56	0.59	0.58	0.65	0.63	0.64
GBM	0.60	0.56	0.60	0.58	0.65	0.61	0.63
MNB	0.69	0.71	0.56	0.63	0.69	0.81	0.75
SVM	0.64	0.61	0.60	0.60	0.68	0.69	0.68
KNN	0.53	0.49	0.81	0.61	0.67	0.32	0.43
RF	0.70	0.70	0.61	0.65	0.71	0.78	0.75
LR	0.68	0.66	0.64	0.65	0.71	0.73	0.72

According to the results of the studies, RF classifier performs well when used with BOW features.

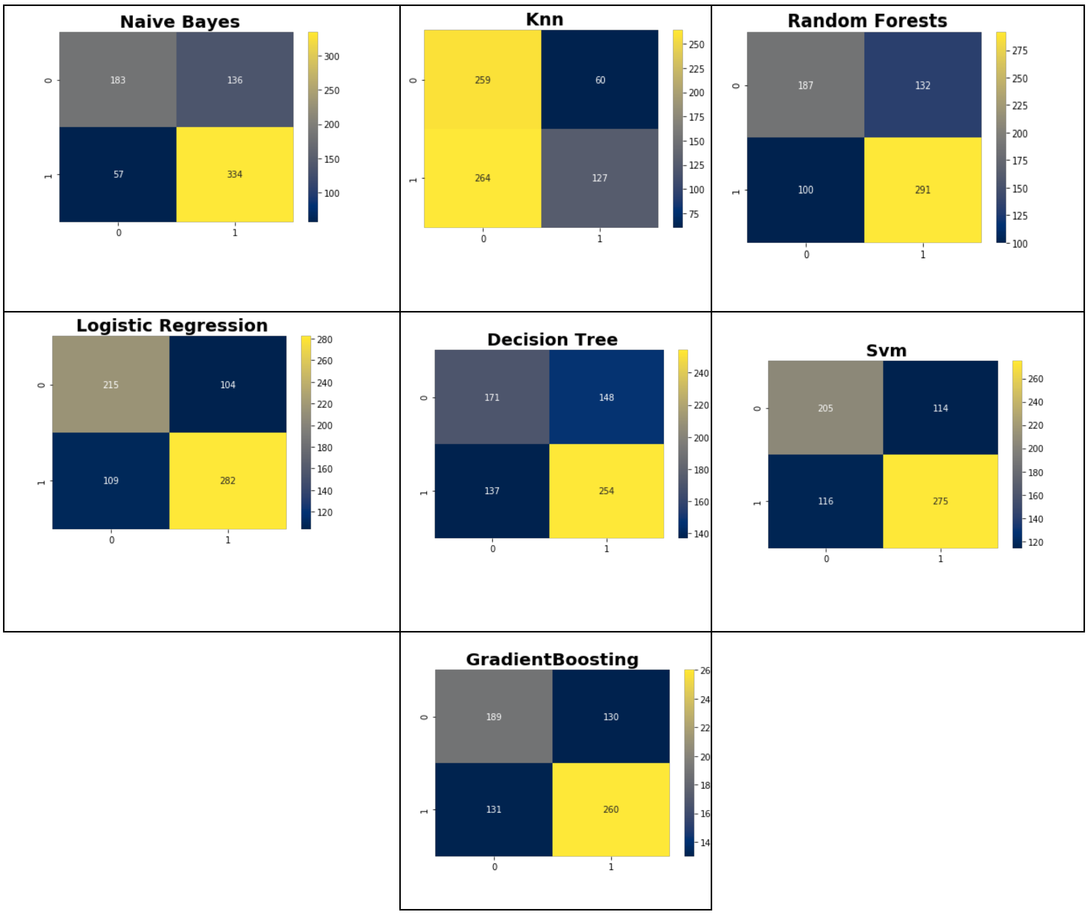

Figure 13. Confusion Matrix with BOW Feature

In this graph, we are comparing the accuracy of all classifier. In this graph, two colored lines are existing; one is red and second is blue. The blue lines are showing the accuracy results of classifiers with TF_IDF feature and red lines are showing the accuracy results of classifiers with BOW feature.

From the graph blue and red lines shows that the accuracy results of classifiers with TF_IDF feature is higher than the accuracy results of classifiers with BOW feature, which was shown in Figure 14.

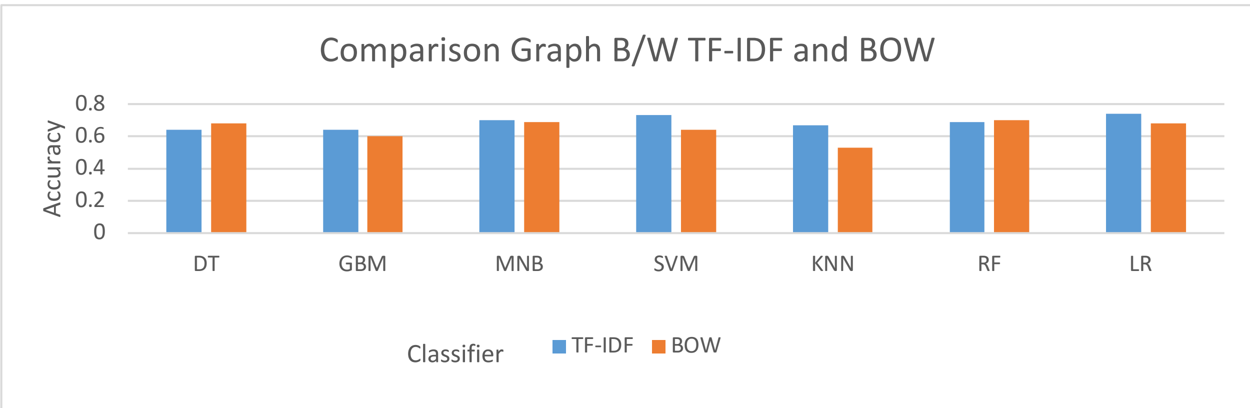

Figure 14. Comparison Graph

5. Conclusions

The aim of this review was to provide readers with an overview of the current state of the algorithms for mental health predictions in the social networks. Most of the studies selected have used text analysis to solve this issue. In some research, image analysis and analysis of social networks have been combined with social media information to provide insights into mental health problems. All of these strategies provide features that can be used to train prediction models and binary classifiers. According to the articles we chose, there was relatively few research utilizing Predictive machine learning models in real social networks to detect individuals with mental problems. Our findings can help in future to develop and validate new algorithms to detect social network users with mental illnesses and to provide the appropriate personalized solution. These actions may take the shape of advertising, information connections, online guidance or cognitive treatment; for example, Facebook is researching at providing real-time online aid to those who are at risk of suicide. Users should carefully consider the validity of the data provided by the social network and the general suitability of these actions.

The future study can include the development and reliability of the prediction with progress made on smart data collection devices, such as mobile phones, clever watches and fitness accessories, as part of physical symptoms, like movement, cardiac signs or sleeping patters, through online social network activity. Finally, researchers interested in this field should pay attention to the ethical issues surrounding human beings and the privacy of data in social networks, as the ethics boards and the public currently fail to understand them.

References

1. Bell, B. S., & Klein, K. J. (2001). Effects of disability, gender, and job level on ratings of job applicants. Rehabilitation Psychology, 46(3), 229.
2. Berle, J. O., Hauge, E. R., Oedegaard, K. J., Holsten, F., & Fasmer, O. B. (2010). Actigraphic registration of motor activity reveals a more structured behavioural pattern in schizophrenia than in major depression. BMC Research Notes, 3(1), 1–7.
3. Berry, N., Lobban, F., Belousov, M., Emsley, R., Nenadic, G., & Bucci, S. (2017). # WhyWeTweetMH: understanding why people use Twitter to discuss mental health problems. Journal of Medical Internet Research, 19(4), e107.
4. Billings, A. G., & Moos, R. H. (1984). Coping, stress, and social resources among adults with unipolar depression. Journal of Personality and Social Psychology, 46(4), 877.
5. Collier, N., Son, N. T., & Nguyen, N. M. (2011). OMG U got flu? Analysis of shared health messages for bio-surveillance. Journal of Biomedical Semantics, 2(5), 1–10.
6. De Choudhury, M., Counts, S., & Horvitz, E. (2013a). Predicting postpartum changes in emotion and behavior via social media. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 3267–3276.
7. De Choudhury, M., Counts, S., & Horvitz, E. (2013b). Social media as a measurement tool of depression in populations. Proceedings of the 5th Annual ACM Web Science Conference on - WebSci '13, 47–56. Paris, France: ACM Press. https://doi.org/10.1145/2464464.2464480
8. D'monte, S., Tuscano, G., Raut, L., & Sherkhane, S. (2018). Rule generation and prediction of anxiety disorder using logistic model trees. 2018 International Conference on Smart City and Emerging Technology (ICSCET), 1–4. IEEE.
9. Ericson, L. W. (2019). OpenSAT19 Pashto SAD/KWS/AST using OpenNMT and PyAudioAnalysis.
10. Faurholt-Jepsen, M., Frost, M., Vinberg, M., Christensen, E. M., Bardram, J. E., & Kessing, L. V. (2014). Smartphone data as objective measures of bipolar disorder symptoms. Psychiatry Research, 217(1–2), 124–127.
11. Giannakakis, G., Marias, K., & Tsiknakis, M. (2019). A stress recognition system using HRV parameters and machine learning techniques. 2019 8th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW), 269–272. IEEE.
12. Grünerbl, A., Muaremi, A., Osmani, V., Bahle, G., Oehler, S., Tröster, G., Lukowicz, P. (2014). Smartphone-based recognition of states and state changes in bipolar disorder patients. IEEE Journal of Biomedical and Health Informatics, 19(1), 140–148.
13. Gupta, R., Malandrakis, N., Xiao, B., Guha, T., Van Segbroeck, M., Black, M.,Narayanan, S. (2014). Multimodal prediction of affective dimensions and depression in human-computer interactions. Proceedings of the 4th International Workshop on Audio/Visual Emotion Challenge, 33–40.
14. Ha, U., Lee, Y., Kim, H., Roh, T., Bae, J., Kim, C., & Yoo, H.-J. (2015). A wearable EEG-HEG-HRV multimodal system with simultaneous monitoring of tES for mental health management. IEEE Transactions on Biomedical Circuits and Systems, 9(6), 758–766.
15. Hanson, C. L., Cannon, B., Burton, S., & Giraud-Carrier, C. (2013). An exploration of social circles and prescription drug abuse through Twitter. Journal of Medical Internet Research, 15(9), e189.
16. Ho, T. K. (1995). Random decision forests. Proceedings of 3rd International Conference on Document Analysis and Recognition, 1, 278–282. IEEE.
17. Husain, W., Xin, L. K., & Jothi, N. (2016a). Predicting Generalized Anxiety Disorder among women using random forest approach. 2016 3rd International Conference on Computer and Information Sciences (ICCOINS), 37–42. IEEE.
18. Husain, W., Xin, L. K., & Jothi, N. (2016b). Predicting Generalized Anxiety Disorder among women using random forest approach. 2016 3rd International Conference on Computer and Information Sciences (ICCOINS), 37–42. IEEE.
19. Jie, N.-F., Zhu, M.-H., Ma, X.-Y., Osuch, E. A., Wammes, M., Théberge, J., Sui, J. (2015). Discriminating bipolar disorder from major depression based on SVM-FoBa: Efficient feature selection with multimodal brain imaging data. IEEE Transactions on Autonomous Mental Development, 7(4), 320–331.
20. Jungherr, A. (2016). Twitter use in election campaigns: A systematic literature review. Journal of Information Technology & Politics, 13(1), 72–91.
21. Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. Business Horizons, 53(1), 59–68.
22. Karam, Z. N., Provost, E. M., Singh, S., Montgomery, J., Archer, C., Harrington, G., & Mcinnis, M. G. (2014). Ecologically valid long-term mood monitoring of individuals with bipolar disorder using speech. 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 4858–4862. IEEE.
23. Kaur, H., & Wasan, S. K. (2006). Empirical study on applications of data mining techniques in healthcare. Journal of Computer Science, 2(2), 194–200.
24. Kawachi, I., & Berkman, L. F. (2001). Social ties and mental health. Journal of Urban Health, 78(3), 458–467.
25. Krieck, M., Dreesman, J., Otrusina, L., & Denecke, K. (2011). A new age of public health: Identifying disease outbreaks by analyzing tweets. Proceedings of Health Web-Science Workshop, ACM Web Science Conference, 10–15. Citeseer.
26. Lockhart, J. W., & Weiss, G. M. (2014). The benefits of personalized smartphone-based activity recognition models. Proceedings of the 2014 SIAM International Conference on Data Mining, 614–622. SIAM.
27. Marcus, M., Yasamy, M. T., van Ommeren, M. van, Chisholm, D., & Saxena, S. (2012a). Depression: A global public health concern.

28. Marcus, M., Yasamy, M. T., van Ommeren, M. van, Chisholm, D., & Saxena, S. (2012b). Depression: A global public health concern.
29. Maxhuni, A., Muñoz-Meléndez, A., Osmani, V., Perez, H., Mayora, O., & Morales, E. F. (2016). Classification of bipolar disorder episodes based on analysis of voice and motor activity of patients. Pervasive and Mobile Computing, 31, 50–66.
30. Moreno, M. A., Jelenchick, L. A., Egan, K. G., Cox, E., Young, H., Gannon, K. E., & Becker, T. (2011). Feeling bad on Facebook: Depression disclosures by college students on a social networking site. Depress Anxiety, 28(6), 447–455. PubMed (21400639). https://doi.org/10.1002/da.20805
31. Nassirtoussi, A. K., Aghabozorgi, S., Wah, T. Y., & Ngo, D. C. L. (2014). Text mining for market prediction: A systematic review. Expert Systems with Applications, 41(16), 7653–7670.
32. O'Brien, J. T., Gallagher, P., Stow, D., Hammerla, N., Ploetz, T., Firbank, M.,McNaney, R. (2017). A study of wrist-worn activity measurement as a potential real-world biomarker for late-life depression. Psychological Medicine, 47(1), 93–102.
33. Ooi, K. E. B., Low, L.-S. A., Lech, M., & Allen, N. (2011). Prediction of clinical depression in adolescents using facial image analaysis. WIAMIS 2011: 12th International Workshop on Image Analysis for Multimedia Interactive Services, Delft, The Netherlands, April 13-15, 2011. Citeseer.
34. Oxman, T. E., Rosenberg, S. D., & Tucker, G. J. (1982). The language of paranoia. The American Journal of Psychiatry.
35. Park, M., Cha, C., & Cha, M. (2012). Depressive moods of users portrayed in Twitter.
36. Parviainen, J., Bojja, J., Collin, J., Leppänen, J., & Eronen, A. (2014). Adaptive activity and environment recognition for mobile phones. Sensors, 14(11), 20753–20778.
37. Paul, M. J., & Dredze, M. (2011). You are what you tweet: Analyzing twitter for public health. Fifth International AAAI Conference on Weblogs and Social Media.
38. Poulin, C., Shiner, B., Thompson, P., Vepstas, L., Young-Xu, Y., Goertzel, B., McAllister, T. (2014). Predicting the risk of suicide by analyzing the text of clinical notes. PloS One, 9(1), e85733.
39. Pramanta, S. A., Prihatmanto, A. S., & Park, M.-G. (2016). A study on the stress identification using observed heart beat data. 2016 6th International Conference on System Engineering and Technology (ICSET), 149–152. IEEE.
40. Reddy, U. S., Thota, A. V., & Dharun, A. (2018). Machine learning techniques for stress prediction in working employees. 2018 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), 1–4. IEEE.
41. Roark, B., Mitchell, M., Hosom, J.-P., Hollingshead, K., & Kaye, J. (2011). Spoken language derived measures for detecting mild cognitive impairment. IEEE Transactions on Audio, Speech, and Language Processing, 19(7), 2081–2090.
42. Rosenquist, J. N., Fowler, J. H., & Christakis, N. A. (2011). Social network determinants of depression. Molecular Psychiatry, 16(3), 273–281.
43. Rude, S., Gortner, E.-M., & Pennebaker, J. (2004). Language use of depressed and depression-vulnerable college students. Cognition & Emotion, 18(8), 1121–1133.
44. Sadilek, A., Kautz, H., & Silenzio, V. (2012). Modeling spread of disease from social interactions. Sixth International AAAI Conference on Weblogs and Social Media.
45. Services, U. D. of H. and H. (2010). Centers for Disease Control and Prevention (CDC) Behavioral Risk Factor Surveillance System Survey Data. 1993–2010 Atlanta, Georgia. Retrieved on January, 10.
46. Usage, T. (2017). Company Facts. 2016.
47. Valenza, G., Nardelli, M., Lanata, A., Gentili, C., Bertschy, G., Paradiso, R., & Scilingo, E. P. (2013). Wearable monitoring for mood recognition in bipolar disorder based on history-dependent long-term heart rate variability analysis. IEEE Journal of Biomedical and Health Informatics, 18(5), 1625–1635.
48. Wang, T., Rudin, C., Wagner, D., & Sevieri, R. (2013). Learning to detect patterns of crime. Joint European Conference on Machine Learning and Knowledge Discovery in Databases, 515–530. Springer.
49. Yu, Q., Miche, Y., Séverin, E., & Lendasse, A. (2014). Bankruptcy prediction using extreme learning machine and financial expertise. Neurocomputing, 128, 296–302.