Exploring Machine-learning Techniques for Early Detection of Depression from Social Media Posts

Nalini Singh[1], Rajnish Pandey[1], Praveen Mishra[1], Shashank S. Tiwari[2], Mariya Siddiqui[1]
[1]*IET, Dr. RLAU, Ayodhya, UP, India*
[2]*REC, Ambedkarnagar, UP, India*

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Abstract: Different social media platforms are trendy among all age groups of people. They post their daily activities regarding the things which have happened to them. People also express their feelings which can be of any kind, such as depressive, sarcastic, irony, and many more. Identifying depression from those social media posts is very difficult work. This work has collected a dataset containing depressive and non-depressive tweets from Twitter and investigated different conventional machine-learning classifiers. Among all classifiers, the Support Vector Machine (SVM) performs better than the remaining and obtained an F1-score of 0.89.

1 INTRODUCTION

The smooth access of distinct interpersonal interaction destinations has empowered anybody to make effortlessly, express, and offer their thoughts, musings, conclusions, and emotions about anything with billions of others around the globe. With the development of innovations, it's entirely possible to share your contemplation about anything via online media stages, for example, Twitter, Wikipedia, Google, Facebook, Instagram, and so forth.

Our work is based on the data collected from Twitter about Depression. We found different situations where a person can go into the depression state smoothly but coming out of it is very hard without professional advice or consulting a psychiatrist. Even though it's a crucial mental issue, not exactly 50% of the individuals who have this wistful issue accessed psychological well-being administrations. Sorrow has gotten one of the predominant psychological wellness issues. This could be a consequence of numerous elements, including having nonattendance of mindfulness about the sickness. One solution would be to create a machine that could detect a person's depression even early. It will help create awareness among people to maintain good mental health. There may be different reasons behind a person getting into the depression state, such as not getting the desired job, due to a family problem, abusive relationship, constant disappointment in the examinations, not getting a healthy working environment, the demise of a loved one's, some other individual issues and, intake of excessive medications also leads to depression.

Depression is a great problem in our community and has continuously been a trending area for sentiment analysis researchers. It is mainly a mental disorder in which people become sad without knowing the reason behind their sadness. People start forming negative thoughts in their minds; they could not concentrate on their work correctly, which creates a sad environment. Depression may cause mental disorders also. It's a severe crippling disorder that might negatively affect humans from all generations, leading to sadness, feeling lonely, and inability to sleep. It is considered the largest factor in global disability and a key reason for suicide. Depression often leads people to commit suicide because they cannot find a solution. And if it is not treated, it impacts people's daily lives surrounded by the individual who's really depressed, as in a family, in the office, or even in our societies. As per the World Health Organization (WHO) study in 2018, over 350 million individuals experienced depression, and just about 1 million individuals with wretchedness ended their lives every year. As per WHO, 4.4% of people are going through a state of

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depression, which is more common in females than males. The use of social networks has increased with the rise in population and communications technology, and they are being used for many different purposes. Here we have used these social networking sites as a source to collect data on depression. In this research, various methods of depression prediction are discussed in depth. The methods involve the collection of a dataset by social media posted texts. From extracted information, the result is obtained.

Here, by identifying and extracting emotions from the text posted through social media (Twitter), using machine-learning techniques, and natural language processing (NLP) techniques, we present a person's level of depression.

Machine-learning procedures might offer some highlights that can help with analyzing the interesting examples covered up in digital channels and cycle them to uncover the state of mentality (for example, 'joy', 'bitterness', 'outrage', 'uneasiness', discouragement) among interpersonal organizations' clients.In this study, we aim to observe the post and determine if the user is depressed. We can further detect other mental problems and might be able to form a mechanism that would assist us with distinguishing and cutoff despondency dispersion in interpersonal organizations. This examination abuses Twitter's data over 10,000 tweets . Different conventional machine-learning classifiers are utilized to recognize the depression level, of which Support Vector Machine (SVM) shows the highest outcomes, with an exactness of 0.91 and F1-score of 0.89. This paper's remaining portion is as follows: Section 2 illustrates the related work. Section 3 explains the dataset. Section 4 describes the different conventional machine-learning classifiers to detect depression. Section 5 tells us about classification approach. Section 6 displays the result of the work. Section 7 is about the discussion. Finally, Section 8 outlines the conclusions and future scope of the study.

2 RELATED WORK

Alsagri et al. introduced a novel approach based on the Linear SVM model. It utilizes Linguistic Inquiry and Word Count (LIWC), sentiment analysis, social activity, and synonyms and achieved an accuracy of 82.5% on the Twitter dataset. Lin et al. also performed their study using Reddit user's data. They employed combined features (LIWC+LDA+ BIGRAM) and N-grams to classify depression records using Multilayer Perceptron (MLP) model and scored an accuracy of 91%. Hassan et al. [4] performed their study on two datasets, the Twitter dataset, and 20newsgroups. In his investigation, By noticing and separating emotions from the text, applying emotion theories, machine learning techniques, and natural language processing techniques, he introduced how to discover an individual's depression level. SVM shows the best results with an accuracy of 91% in comparison to Naive Bayes and Maximum Entropy classifiers. Guntuku et al. introduced a new approach based on the Neural Network model in which it utilizes N-grams features and reached an accuracy of 70% on the Twitter dataset. Arun et al. exhibit a novel methodology for identifying depression using clinical information from the on-going Mysore investigations of Natal consequences for Aging and Health (MYNAH). The proposed model was created, utilizing XGBoost and an accuracy of 97.80% by using feature selection on the accessible information of evaluations with improved certainty. Khan et al. referenced a framework that predicts and calculates the Bengali text's sentiment that was obtained from Facebook. They utilized machine-learning classifier algorithms to locate the best exactness and identify the two sorts of groupings as happy and sad. In the wake of preprocessing the information, they tokenized the data by utilizing Countvectorizer. They applied six different algorithms to foresee the most noteworthy exactness from that point onward. Among them, the Multinomial Naive Bayes gave us the most excellent accuracy of 86.67%. Peng et al. proposed a multi-kernel SVM-based model. It utilizes three feature categories: user micro-blog text, user profile, and user behaviours and gained an accuracy of 83.46%. Nadeem et al. conducted their study using 2.5M tweets. He employed features such as bow and sentiment analysis using the Naive Bayes model and scored an accuracy of 81%. Jain et al. worked on two different depressive datasets. One is based on the questionnaire and another on Twitter.

Table 1: Some potential work on depression

AUTHOR	FEATURES	MODEL	PER.
AlSagri et al. [2]	LIWC Sentiment Analysis Social Activity Synonyms	Linear SVM	Acc: - 82.5%
Lin et al. [3]	Combined features (LIWC+LDA+BIGRAM) N-gram	Bi-gram with SVM	Acc: - 91%
Hassan et al. [4]	N-grams Parts of Speech Negation Sentiment Analyzer	SVM	Acc: - 91%
Guntuku et al. [5]	N-grams	Neural Network	Acc: - 70%
Arun et al. [6]	Eurotot Avggrip HTN Frifrailtylot BMI	XG Boost	Acc: - 97.80%
Khan et al. [7]	Countvectorizer	Multinomial Naive Bayes	Acc: - 86.67%
Peng et al. [1]	TF-IDF	Multi-kernal SVM	Acc: - 83.46%
Nadeem et al. [8]	Bow Sentiment Analysis	Naive Bayes	Acc: - 81%
Jain et al. [9]	Age Sex Regularity TF-IDF etc	XGBoost Logistic Regression	Acc(q): - 83.87% Acc (Twitter): - 86.45%
Asad et al. [10]	TF-IDF NLTK	Naive Bayes	Acc: - 74%

They performed different conventional machine-learning classifiers. Among them, XG Boost performed better on the first dataset with an accuracy of 83.87%, and Logistic Regression performed better on the second dataset with an accuracy of 86.45% on the Twitter dataset. Asad et al., in their proposed model, data is gathered from user posts on two web media sites: Twitter and Facebook. They employed TF-IDF features on the Naive Bayes model and scored an accuracy of 74%.

3 DATASET

3.1 Data Collection

To collect depressive tweets, we extract tweets with hashtags #depression and #sad quotes using Twitter and manually select English tweets. We also used other specific words like 'misery', 'unhappiness', and 'sorrow' to collect depressive tweets from this domain. Out of these collected tweets, depressive and non-depressive tweets are further manually separated. To gather more non-depressive tweets, we extracted tweets with keywords such as 'misery', 'unhappiness', and 'sorrow' which do not contain hashtags# depression and #sad quotes. Further English tweets were manually selected from them. Having only depressive or only non- depressive tweets from a particular do-main may lead to an unbiased classification system; therefore, we made sure that there were both depressive and non-depressive tweets from each domain.

3.2 Data Processing and Annotation

Tweets are annotated by a group of people fluent in English. Each tweet is manually annotated for the presence of depression.

Depression Annotation Each tweet is manually annotated for the presence of depression using the tags' YES' and 'NO'. Tweets with the hashtags #depression are more likely to contain depression. Tweets that do not include these hashtags are then manually verified to manage depression. Here is an example of a tweet (with translation in English) that contains depression and one that does not:
Tweet: #depressive... I'm very upset.

Depression: YES

Tweet: #normal quotes... I'm very happy.

Depression: NO

Hashtags #depression is randomly deleted from some tweets which contain depression so that the dataset includes depressive tweets with the hashtags #depression and some without the hashtag.

3.3 Dataset Analysis

The dataset consists of 12,029 English tweets, out of which 5,529 tweets are labelled as depressive and 6,500 non-depressive. The dataset consists of two types of tweets:
1. Tweets that are depressive but do not contain hashtags #depression.
2. Tweets containing hashtags but not considered as depressive.
This sparsity in the corpus also helps develop a better system for depression detection. The average length of a tweet is 22.2 tokens per tweet. The

detailed descriptions of this dataset can be seen in table 2.

Table 2: Data Statistics

Class	User Collected Dataset
Depressive	5,529
Non-depressive	6,500
Total	12,029

4 DEPRESSION DETECTION SYSTEM

For the detection of depression in English tweets, we have used a baseline classification system in which word-based features was used to identify the level or type of depression. Further, these features were observed via machine-learning techniques to detect depression.

4.1 Preprocessing

It is a typical practice via online media to utilize camel cases while writing hashtags. Along these lines, we extract the hashtags from each tweet and extract separate tokens from it by eliminating the '#' and utilizing a hashtag deterioration approach, accepting it is written in camel case. For example, we can get 'I', 'Am', and 'Depressive' from '#IAmDepressive'. URL's mentions, stop words, and punctuations are taken out from tweets for further processing.

4.2 Features

Word N-Grams: Word n-gram indicates having or not having a continuous sequence of n-word or tokens in a tweet. Word n-grams have been demonstrated to be valuable features for depression detection in previous experiments. We consider all n-grams for estimations of 'n' from 1 to 5. We consider just those n-grams for features that happen at least ten times in the corpus to prune the feature space.

5 CLASSIFICATION APPROACH

We have used seven different conventional machine-learning classifiers such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR), Gradient Boosting (GB), and Naive Bayes (NB). We use the scikit-learn implementation of these methods for depression detection.

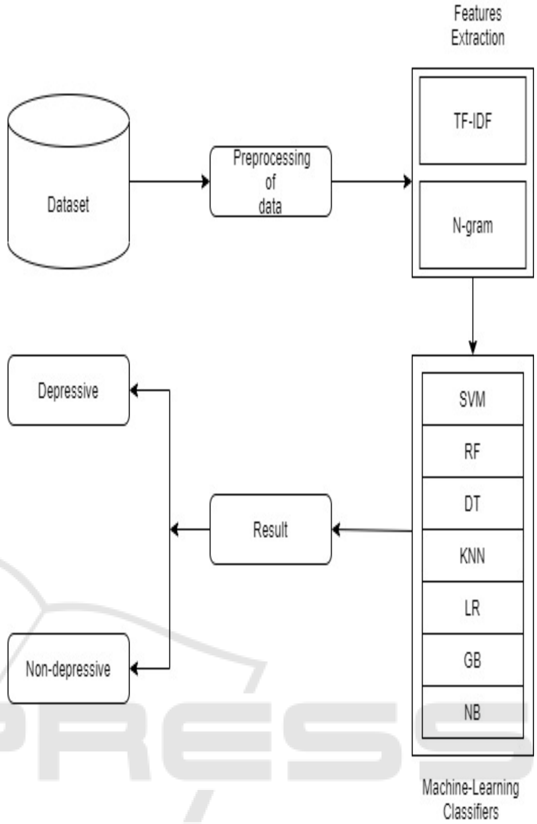

Figure 1: Structure of Depression Detection

6 RESULT

On doing extensive experiments on the collected dataset, it is found that the different conventional classifiers achieve acceptable performance. The Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR), Gradient Boosting (GB) and Naive Bayes (NB) achieves an F1-score of 0.89, 0.72, 0.79, 0.62, 0.88, 0.81 and 0.84.

The mathematical equations for the precision, recall, and F1-score can be seen from following equations.

Precision(depressive)=

$$\frac{Number of accurately predicted depressive sentences}{Total number of predicted depressive sentences}$$

Recall(depressive)=

$$\frac{Number of accurately predicted depressive sentences}{Total number of actual depressive statements}$$

F1-Score=$2\times\frac{Precision\times Recall}{Precision+Recall}$

Table 3: Result of Conventional Machine-Learning Classifiers

		Performance		
Models	Class	Precision	Recall	F1-score
SVM	Depressive	0.86	0.86	0.86
	Non-depressive	0.91	0.91	0.91
	Weighted	0.89	0.89	0.89
RF	Depressive	0.93	0.39	0.55
	Non-depressive	0.71	0.98	0.82
	Weighted	0.80	0.75	0.72
DT	Depressive	0.75	0.72	0.73
	Non-depressive	0.82	0.84	0.83
	Weighted	0.79	0.79	0.79
KNN	Depressive	0.91	0.23	0.37
	Non-depressive	0.66	0.98	0.79
	Weighted	0.76	0.69	0.62
LR	Depressive	0.86	0.84	0.85
	Non-depressive	0.90	0.91	0.90
	Weighted	0.88	0.88	0.88
GB	Depressive	0.87	0.63	0.73
	Non-depressive	0.79	0.94	0.86
	Weighted	0.82	0.82	0.81
NB	Depressive	0.75	0.91	0.82
	Non-depressive	0.93	0.80	0.86
	Weighted	0.86	0.84	0.84

7 DISCUSSION AND LIMITATIONS

The significant finding of this research is that the proposed analysis of conventional machine-learning classifiers is analyzed for identifying depression in the case of the user-created dataset. From the result table number: 3, it is evident that the SVM is performing well as compare to another remaining conventional machine learning classifier. The SVM achieved an F1-score of 0.89. Whereas in the case of KNN classifier is achieved an F1-score of 0.62 that is worst among all conventional machine-learning classifier. The recall of 0.89 for the depressive class means that the SVM can identify depressive symptoms in 87 cases out of depressive tweets.

Several similar works [12, 13, 14 and 21] are also reported for identifying depressive sentences from Twitter.

Alsaleem et al. [22] proposed a new technique based on the SVM model. It utilizes features such as Arabic prefixes, pronouns and prepositions and achieved an accuracy of 77.8% on the Arabic dataset.Liparas et al. [15] proposed a model in which the data is collected from the News Articles. They employed N-gram and (Textual + Visual features) on the Random Forest model and scored an accuracy of 86.2%. Hussain et al. [16] employed feature Frequency Counter of Ambiguous Keywords and Valid features using the decision tree model and gained an accuracy of 75.7%.

One of the limitations of this work that is that we have only used English language sentences to train our model. However, several depressive messages are also posted in regional languages on social media. Another limitation of this work is that we have only used textual content from the tweets to identify the depressive sentences. Social media post also contains emoji's, hyperlinks images and videos, which are not taken into accounts in the current research.

8 CONCLUSION

Identifying depression from the textual contents is challenging in the natural language processing area. The performance of the SVM outperforms several conventional machine-learning classifiers. The current research can also be extended to include the other modalities present in a social media post, such as images, videos, and audio clips. The inclusion of emoji's and other hyperlinks present in a social media post can also be validated.

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