|| Volume 6 || Issue 3 || March 2021 || ISO 3297:2007 Certified ISSN (Online) 2456-3293

OPEN ACCESS INTERNATIONAL JOURNAL OF SCIENCE & ENGINEERING

MACHINE LEARNING BASED ON APPROACH FOR DETECTION OF DEPRESSION USING SOCIAL MEDIA USING SENTIMENT ANALYSIS

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Abstract: Facebook, Twitter, and Instagram, among other social media platforms, have irrevocably changed our world. People are more linked than ever before, and they have developed a digital character. Although social media has a number of appealing qualities, it also has a number of drawbacks. Recent research has found a link between excessive use of networking platforms that are social and greater depression. The aim of this research is to apply techniques of machine learning to identify a likely sad user of Twitter who is based on his or her behavior of network & tweets. The goal of this research is to apply techniques of machine learning to detect a possible unhappy Twitter user's tweets. We used variables collected from a user's behaviors within tweets to train & test Classifiers to differentiate that a person is depressed or not. On a scale of 0-100 percent, classification machine algorithms are used to train and classify it in different stages of depression. Also, data were collected in the form of tweets, which were categorized into whether the person who tweeted was depressed or not using Machine Learning classification algorithms. Predictive technique for early identification of depression or other diseases related to psychological in this way. The key contribution of this study is the investigation of a neighborhood of features and their consequences on finding levels of depression.

I INTRODUCTION

Depression is a prevalent mental condition that can lead to suicide. It is also a primary cause of disability worldwide. Every year, it is estimated that more than 30 crore people worldwide suffer from depression1. Depression is typically diagnosed using the criteria of clinical depression directly on the face. However, in the early phase of depression, 70 percent of people do not seek medical help, which leads to their disease progressing [1].

There has recently been a push to use social media data to detect, estimate, and track changes in the occurrence of diseases [2]. Because of its widespread use, social media offers a wealth of opportunities to improve the available data to practitioners of mental health and analysts, resulting in a well-equipped field of mental health [3]. Furthermore, people are negatively affected by negative emotions in social networks which are harmful, which can lead to depression and other psychological problems. The risk of suicide has been identified for mental illness; approximately 80 percent have been diagnosed with the mental disease for persons who try or die by suicide [4, 5]. The most frequent illness related to mental disorder is Depression [6], yet it has gone undetected or untreated due to a lack of acknowledgment or denial [7}. Early detection of major depression symptoms and therapy with prompt intervention can assist to prevent major depression from developing. [7].

As a result of the huge amount of data available on social media, There has been much research that has discovered physical and mental disorders, with some studies focusing specifically on depression [3, 8, 9]. People with severe depression's Tweets, as well as their social media behavior, can be used to detect and forecast whether they will be depressed in the future, according to De Choudhury et al. [8]. Tsugawa et al. and Coopersmith et al. looked at the user's Twitter activity [3, 13], whereas Nadeem et al., Dredze et al., and Benton et al. looked at whether or not the user's tweets were depressed [10-12].

This research also seeks to determine that the user is sad based on the content of his or her tweets & activities of social media networks. It could also be used to recognize other diseases of mental disorder, & it could even serve as the foundation for new techniques to find and diffusion of control depression in social media networks.

This research uses information from 111 user-profiles and over tweets of number 300,000 tweets. To determine the severity of depression, a variety of classifier algorithms are used, with the best results coming from the support vector machine (SVM)-linear, which has an accuracy of 82.5 and an F-measure of 0.79.

The following is how the rest of the study is structured: The literature review is depicted in Section 1. The scientific underpinning of the classifiers utilized in the experiments is presented in the 2nd section. The research method, as well as the features retrieved and computed, are explained in Section 3. The experiments are described in Section 4 and the findings are discussed. Finally, section 5 summarises the study's findings.

II LITERATURE OF REVIEW

With the rise in usage of social platforms & the high amount of self-disclosure on these social platforms, attempts to diagnose depression from data from Twitter have grown [9, 14]. According to Park et al. [15], Users of Twitter who are likely to be depressed are more likely to post tweets with negative emotions than the users that are healthy. Furthermore, De Choudhury et al. [8] discovered that signs of depression can be detected in tweets written by people suffering from serious depression [9, 10, 16].

Numerous characteristics have been used to diagnose depression using data related to Twitter to date. De Choudhury et al. [8] gathered over two million tweets from 476 clinically depressed individuals who also had Twitter accounts. They studied behavioral aspects associated with social engagement, sentiments, styles of the linguistic, network of ego, and mentions of medications related to anti-depressants in order to develop a classification that gives estimations of the danger related to depression. They exploited such distinct properties to develop a classifier of SVM that is 70% accurate in predicting depression. Tsugawa et al. [13] demonstrated the importance of word frequency and topic modeling in the prediction model. They obtained a classification accuracy of 69% when predicting depression in 81 of the 209 people who completed a questionnaire. Additionally, using supervised learning algorithms, Reece et al. [9] done the extraction of anticipated variables for evaluating the impact, style of linguistic, and context from tweets of the user, developed models including these features, and successfully differentiated b/w sad & healthy contents. The CESD scores were calculated using data from 105 of 204 depressed users. In comparison to other study outcomes when a 1200-tree random forest classifier was applied, the performance of the best classifier was discovered, boosting the precision to 0.866. To improve the detection of depression, Nadeem et al. [10] picked the bag-of-words method, which quantifies the content of a tweet at the document level using word occurrence rates. As four distinct Binary classifiers, they looked at the linear SVM classifier, the decision tree (DT), the Naive Bayes (NB) technique, and logistic regression. They observed that the NB algorithm outperformed the others, with an accuracy of 81 percent and a precision of 0.86 percent. They examined a corpus of more than 2.5 million tweets from users who expressed dissatisfaction with the CLPsych 2015 Shared Task Organizer. (326) or had post-traumatic stress disorder (PTSD) (PTSD). Researchers such as Nadeem et al. [10] and Coppersmith et al. [3] have looked into sentiment analysis as a feature for using Twitter data to diagnose depression. Other academics, such as Mowery et al. [2] have looked explored using sentiment analysis as a tool to identify depression using Facebook data. According to Jamil et al. [14], combining sentiment analysis with the percentage of depressed tweets improves diagnosis accuracy and recall for depression in Twitter. SVM was used to train the classifier on 95 individuals who self-identified as depressed (5 percent of study participants; the remaining 95 percent were healthy users), and the findings indicated that it had an accurate recall rate of 0.875 and an accurate accuracy rate of 0.775.

De Choudhury. et.al.[8] & Jamil. et.al. [14]Extracted attributes from sad tweets of peoples to increase the accuracy of detection. De.Choudhury. et.al. [8] created a depression lexicon, which includes words that are likely to appear in Internet posts by individuals discussing depression or its symptoms. Jamil. et.al [17], on the other hand, used the percentage of depressed tweets as well as (self-indication)of depression to determine whether an account user should be excluded from a set of training and observed that doing so improved the model's accuracy.

III METHODOLOGY

Nowadays, Social media networking sites are the new knowledge gateway for all age groups. It has become a manifesto to express sentiments in the form of opinions, judgments, feelings, expressions, and reviews on almost everything such as movies, brands, products, and clothing industry, social – activities, and so on. The reviews or expressions can be positive, negative, or neutral. The automated process of analyzing these opinions or text of data is known as ‘Sentiment Analysis’.

“Sentiment Analysis can be delineated as a standardize analysis of online expressions.”

There are a plethora of approaches and strategies for detecting depression levels from posts on social media networks, and the list is expanding. In this paper, we summarise a description of technical approaches used to detect sadness utilizing Natural Language Processing (NLP) and text classification algorithms. The framework is comprised of Data pre-processing step, the Feature extraction step following the Machine Learning classifiers, the Feature analysis of the data, and Experimental Results.

3.1 Dataset

The dataset consists of tweets collected using the (API) Application Programming Interface twitter. We have collected a total of 15,000 Tweets for the generation of the training module and testing module for our model. We will exercise a ratio of approximately 70:30 for splitting the data collected from Twitter API into training modules and testing modules. Two word-records will be compiled for the training and testing datasets for the classification. The training record comprised of a systematized list of words demonstrating mental illness such as depression proclivity like 'depressed', 'sad', 'suicide', 'gloomy', 'unhappy', 'low', 'down', 'heartsick', and many more. For the testing dataset, we will include tweets that are collected at random which will include neutral as well as negative components.

3.2 System Architecture

In order to detect whether the user of a Twitter account is sad based on tweets from Twitter behavior, a study of quantitative analyses was conducted to train & test many classifiers of machine learning.

Different R programs are used for the processing, extraction, and classification of data. To avoid overfitting, the classifier is trained and using ten-fold cross-validation & then evaluated on a set of tests to guarantee accuracy.

The detection of depression utilizing a model of activity and content classification characteristics is presented in figure (1).

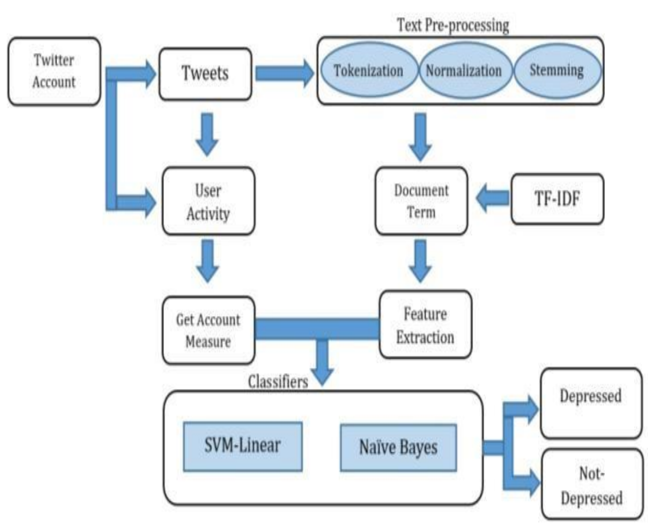

Fig 1: Architecture of the system

To begin, all tweets from the account of depressed & non-depressed users are retrieved, as well as user account and activity information such as no. of followers, time of posts, number of mentions, and no. of retweets. Following that, all of an account's tweets are compiled into a single document.

All documents are subjected to text pre-processing. To start with, a compilation is produced & tweets are tokenized for each document. The next step is to normalize all of the characters and to remove punctuations, retweets, mentions, links, unknown emoys, and symbols. Stop words like "I," "me" and "you" are typically deleted during normalization, but we maintain pronouns of the first person. Subsequently, stemming is employed for each account to build a document term matrix (DTM). Each row represents all of the words used in all accounts, and the matrix indicates the number of words in each tweet. To measure the weight of words, TF-IDF is utilized.

After that, account metrics derived from the network of social media & user behaviors are combined with features applied to the DTM. The result from a merging is then utilized to forecast the dependent variable of the intended outcome as an independent variable in a classification algorithm. Finally, we select a vector classification of the DT, a linear kernel, and an NB algorithm because a study shows that SVM and NB classifiers are the most accurate. [6]. The following figure shows the graph of Depression Detection Accuracy of various classifiers.

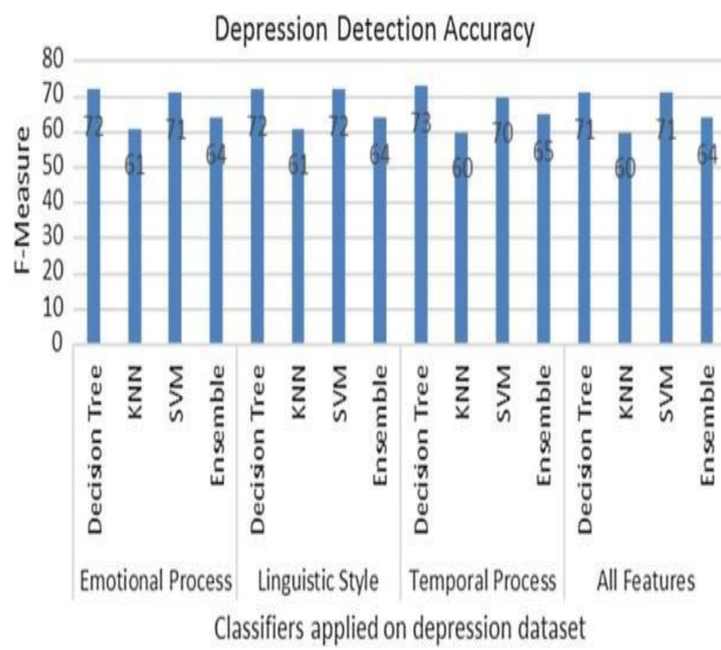

Fig 2: Depression Detection Accuracy

3.3 Data Pre-Processing

Pre-processing data is a necessary step in building a Machine Learning model and counting on however well the information or text data has been pre-processed; the results square measures are seen. And if it involves unstructured information like text, this method is even a lot necessary.

Before proceeding to the feature selection and training step, we employed (NLP) "Natural Language Processing techniques to preprocess the dataset. To segregate the tweets from Twitter into unique tokens in the initial phase of preprocessing data, we utilize the Tokenization method. After that, all URLs, punctuations, and stop words are removed. that, if disregarded, could result in unpredictable results. For Sentiment Analysis of the text for depression detection, we need not remove the emojis or emoticons as it can convey some important information about the sentiment. Then we tend to apply stemming so as to scale back the words to their root type and cluster similar words along.

3.4 Feature Extraction

To provide output for the check information, algorithms of Machine Learning learn from a set of pre-defined alternatives from the data of training. The main drawback of using language processing is that machines can't work with the raw text directly. So, to transform the text into a vector of alternatives, we need some feature extraction techniques.

Some of the foremost in style ways of feature extraction included are:

•Bag-of-Words

•TF-IDF

A] Bag of Word:

The models of the bag of the word maybe simplify the illustration employed in tongue process & data retrieval (IR). During this model, a text is delineated because of the bag of its words, disregardless of synchronic linguistics and even order however keeping multiplicity.

In a process of depression detection analysis of sentiments, the appearance of the words like ‘joyful’, ‘happy’,

‘amazing’ shows a positive response towards life, while words like ‘sad’, ‘depressed’, ‘dejected’, ‘sorrowful’, ‘miserable’ point to a negative response.

There are basically three steps that are included in the creation of a model of Bag of Words:

A) The first step involved in preprocessing of text are:

1. Changing all of the characters in the text to lower case.

2. Eliminating any unneeded punctuation and symbols.

B) The second phase entails creating a vocabulary that includes all of the collection's unique words.

C) In the third stage, we generate a feature matrix by allocating a separate column for each phrase and a row for each sentiment. Text vectorization is the term for this procedure. The existence (or absence) of a word in the Sentiment is indicated by each item in the matrix.

B] Inverse Document Frequency (IDF) :

(TF-IDF) is a method that seeks the word-consistent meaning in the Bag of Words technique which is sweet for text classification or to be served in numbers for scanning machine words. TF-IDF or (Term Frequency (TF)).

C] Parts of Speech (POS) Tagging :

Speaking part Tagger is a software that reads and assigns components of each word to the text in a particular language, for example, names, verb adjectives, etc.

IV ALGORITHMS

Machine Learning Classification Techniques used for the model:

4.1 Naïve Bayes :

Classify Naïve Bayes The analysis of sentiments could be a field devoted to the extraction of subjective emotions and feelings. One typical use of sentiment analysis is to determine if a text expresses positive or negative sentiments. Written reviews unit of beautiful data sets for sentiment analysis because they usually have a score that does not train a rule.

4.2 Machine Support Vector:

Support Vector Machines is an algorithm that determines the most effective call boundary between vectors that belong to a given cluster (or category) and vectors that don't belong thereto. It will be applied to any reasonable vectors that inscribe any reasonable knowledge.

V CONCLUSION

Finally, we show whether users discuss their depressed feelings or disclose their depression on widely-used channels like Twitter. We have developed a prediction algorithm to determine whether or not a user's tweet is depressed based on a supervised method for sentiment analyzing detection of deprived people. We tested the performance of all four classifiers on the basis of manually created corpuses with true labels acquired by Twitter in the Gulf Region (depressed, non-depressed). We found that depressed individuals are more socially isolated than shown by how they connect with popular hashtags used in their tweets. We have also studied how they interact.

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