SENTIMENT ANALYSIS TO DETECT DEPRESSION IN SOCIAL MEDIA USERS: OVERVIEW AND PROPOSED METHODOLOGY

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Abstract. This paper reviews the different methods that are used in sentiment analysis for detecting depression in social media users. Sentiment analysis of the text is generally executed sequentially: every set of text is broken down progressively into components such as sentences, phrases, and words. The tokenized text is then processed such that each component of speech is identified for its sentiment and then assigned a score in the range of -1 to 1, with -1 indicating the most negative emotion and +1 indicating the most positive emotion. The aggregate score of the entire text is then used to determine the overall sentiment of the text. The paper outlines a proposal of a cumulative analysis method to detect the depression level of a person by extracting data from social media posts in conjunction with other data pertaining to the user such as sleep, food intake and exercise patterns. The proposed method performs a multi-varied analysis on the type of emotion exhibited by the data using machine learning techniques on extracted data for a given user.

Keywords: Depression · Sentiment analysis · Cumulative analysis · Twitter.

1 Introduction

Despite the fact that it is quite a prevalent mental health disorder, depression is the most under-diagnosed disorder due to the lack of proper testing and the social stigma surrounding it. The WHO gives an estimate that nearly 264 million people under all age groups suffer from depression. The WHO ranks depression as one of the most burdensome diseases in the world. [1]

Depression has a wide range of symptoms which include symptoms of anxiety, disturbed sleep. It also includes hyper insomnia and insomnia and loss of appetite, guilt, low self-worth, and loss of interest in activities that were enjoyable. The symptoms worsen depending on the severity of the disorder and may lead to bipolar affective disorder (BAD). Depression is also known to affect other present chronic conditions like cancer, diabetes, and cardiovascular diseases along with affecting the social life of an individual and interpersonal relationships. [2] Severe depression may also lead to suicide. [3]

Diagnosis and proper treatment of depression can greatly improve the condition; however, it is quite difficult to diagnose it at a population-level, and a tedious, time-consuming, and expensive task. Under such circumstances, social media provides a treasure trove of behavioural information holding data relevant to the detection of depression in users. Social media depicts attributes that are relevant in capturing the mood and thinking patterns, communication, and socialization. People suffering from depression tend to withdraw themselves from social situations and activities. Their emotions and language can be traced via their posts which may indicate feelings of hopelessness, guilt, suicidal expressions, self-hatred, and helplessness. These are all indicators of a severe onset of depression. [2]

Twitter is one such social media platform that allows its users to microblog with up to 120 characters per blog. It has a wide variety of topics ranging from politics to health. It is deemed to be most appropriate for research in the mental health domain as mental health research requires study related to behaviour which includes the way they interact and engage with other users online including their friends and family. Research via the capture of population-level behavioural trends from online data has been used by health researchers successfully. [4] Several studies on mental health and depression detection have already been performed using Twitter data as the predominant data source. [5] The extraction of such data is called sentiment analysis, which is basically a tool to gauge the attitude, emotion, sentiment and opinions of an individual through information written by them. More details on sentiment analysis and its use cases can be found in [6] However, even with extensive work done on this subject, there are several loopholes that make this method of detection unstable if it were used on a larger scale. In our review we aim to answer the following questions:

1. RQ1: Is there any established framework or methodology to detect depression through Twitter analysis?
2. RQ2: Is there any way to improve the quality of data and make the data more reliable?

In order to investigate these questions, we have conducted a Systematic Literature Review (SLR) in hopes of improving the currently available technology to make it more user-friendly, reliable, and provide greater accuracy.

2 Related Work

2.1 Background Literature

Throughout history, several offline social networks of individuals have been studied in order to analyze behavioural changes related to the psychological environments. The roles of stress in social situations and methods to cope with them for individuals undergoing treatment for depression have been studied by Billings and Moo. An intake of less than 500 kcal/day can lead to glycogen stores being mobilized in the body and 24h fasting can cause lipolysis and accelerated protein catabolism. [7] Studies have suggested that fasting in order to decrease body weight can facilitate depression. Restricting calories may impair cognitive abilities and lower overall quality of life resulting in stress and an elevation of the level of corticosterone [8, 9] which may lead to an increased risk for depression.

The correlation between sleep and behaviour exhibited by a person has been extensively researched over the years. For instance, people suffering from insomnia are prone to having higher levels of depression and anxiety than those with normal sleep schedules. They are 10 times as likely to have clinical depression and 17 times as likely to have clinical anxiety than the average person with a regular sleep schedule.

Oxman [10] showed through his research that the linguistic analysis of speech could classify individuals into groups of those who were not suffering from depression and those who were. Similar results are obtained under a computerized analysis of a written text. This opens the door to utilizing social media for analyzing mental health. NLP can be applied to obtain relevant results and make predictions with around 80 percent accuracy. [2, 11]

Twitter has been widely used in studies to show that individuals who score high in depression scales tend to have differences in writing which is quantifiable with LIWC. Individuals suffering from depression often make extensive use of depression-related words and emotions when compared to their normal counterparts. [12]

2.2 Data Collection Techniques

Upon survey of quite a few papers that use Twitter as a medium for detecting depression, the following trends have been observed with regards to the various methods used to collect relevant data. Some of the most prevalent ways are:

1. Crowd-sourcing: Crowd-sourcing [2, 11] is used in order to study the control group of users with verified history with depression or at its onset. This also helps to decrease the ethical concerns with studying such data and reliability issues with information collected, however, its issues with scalability leave more to be desired. This often leads to the application of supervised machine learning algorithms where all the required data is labelled and given in the form of a training data set to the system.

2. Twitter API: Twitter API [3, 13] is used in order to extract all public data ranging from a specific time period. This is further preprocessed by identifying those with emotion-related hashtags in order to extract relevant information. This makes most of the work extremely tedious and in order to create a control group, in most cases, human coders were required to verify the tweets manually. This leads to the implementation of semi-supervised machine learning algorithms where a small amount is labelled and combined with a large amount of unlabelled data and given as a training data set to the system.

2.3 Classification And Identification Techniques

Among various techniques used to classify a user as depressed, the most relevant and predominant are Classification frameworks based on LIWC (Linguistic Inquiry and Word Count):

1. LIWC is a tool used to quantify data regarding the mental state of a patient from their writing. It has been extensively used in research regarding sentiment analysis. This is further used to predict tendencies in psychiatric disorders and neurotic tendencies. [14] The data extracted from the tweets are labelled in accordance with LIWC standards mainly into words having a positive affect and those having a negative affect. These are further subdivided based on the experiment, usually to flag the level of negativity expressed by the rates explained in LIWC. [14, 15] These are then scored and individuals with a higher score with words categorized as negative, are flagged as either strongly concerning, possibly concerning, or safe to ignore [3].
2. Machine learning classifiers:

   a) Support Vector Machine (SVM) classifier: This classifier is used in supervised learning for classification and regression. Twitter posts are represented as vectors of features which include a variety of conditions to fit into a feature which has been highly researched as common behaviours among people displaying depression, like duration of use, as people suffering from depression tend to be active during the night [2], hashtags, language expression, emotional context and level of engagement and tokenized for feature extraction. Using this, the accuracy of more than 70 percent was achieved in predicting depression, by [11] and [16]. Since it is a supervised learning algorithm, all the required data and features were labelled and then provided to the training data set.

   b) Multinomial Naive Bayes (MNB) and Liblinear classifiers: This classification system was used in conjunction where the MNB classifier outperformed Liblinear inaccuracy by [5]. MNB works extremely well with data that can be turned into counts. It gives the probability of the occurrence of a word or feature which is then used to determine the severity of the situation depending on LIWC. Liblinear is a linear classifier for data with huge amounts of features. Since it is an implementation of SVM, it works very similarly to it, wherein it gives the feature probabilities. Both these algorithms work very similar to SVM, however, the main reason for selecting these algorithms is because of their ability to scan and classify a massive number of Tweets which is essential in scaling the operation of detecting depression at the population level.

3. Human Coding: In this method, coders were asked to analyze and classify tweets as concerning and not concerning. These were further subdivided, and the implementation was done on a small sample of 100 tweets. This human coded data for classification was later used by machine classifiers as training data which could automatically detect the category of concern.

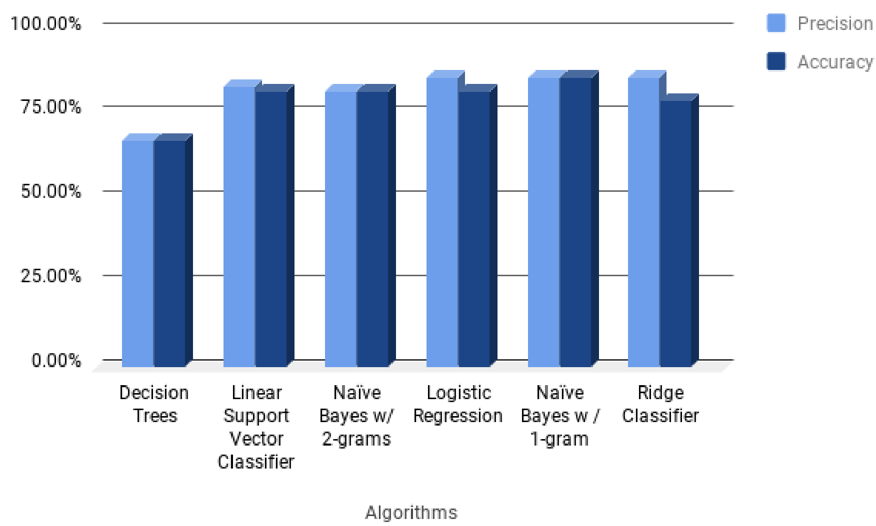

Fig. 1. Precision and Accuracy for different classification models [17]

2.4 Advantages

1. Easier detection on population-level: It provides a less expensive and less tedious larger scale detection system for depression that can be used to provide resources.
2. Likelihood prediction: Not only can it identify depression; it can also predict the likelihood of having depression in the future. This could highly improve the way mental health is treated and diagnosed in the future [11].
3. Increased accuracy: As the data-sets used for training increase, the accuracy of prediction also increases [5].

4. Identification via ego-networks: After detecting one individual, their ego network (a group of people they interact with the most) can also be analyzed and as shown by [11] This leads to faster rates of detection.

2.5 Disadvantages

1. Ethical and privacy issues: Ethical concerns like privacy issues come into the picture, as extracting information without the user's consent, even if it is public information. Most users suffering from depression would be reluctant to allow such extraction of information. This has been mentioned as a cause of concern in [2, 3, 11, 13]. Until there is a great deal of advancement in cyber-security, the privacy of any user cannot be ensured.
2. Lack of sophisticated analysis: Despite LIWC being a highly sophisticated language classification tool, the context of literature becomes irrelevant when the user is tweeting sarcastically. The context of the tweet matters a lot, and this leads to false positives; wasting valuable resources and time.
3. Small test group size: Most of the research done in the domain has used a rather small size of participants to perform the experiments. This makes the results obtained highly unreliable as usually drastic changes are observed on increasing the number of participants, features, or even the range of time during which the experiment is carried out. The accuracy provided by any of the models does not exceed 80 percent.
4. Unreliable: Reliability also comes under question when figuring if personality portrayed online actually relates to a person's real personality. Most people tend to showcase an ideal image of themselves on social media, and tweets can be deleted, which again leads to unrequired data as none of these methods focus on updating information that has already been collected.
5. Lack of language identification: The classifiers only work in English which ignores several languages that are also used on the platform to micro-blog. Some tweets are typed in English, but they are in other languages which are undoubtedly not recognizable by LIWC or any such tool.
6. Lack of any standard framework for detection: In order to make this approach readily accessible to medical professionals, there needs to be a standardized approach to determine the accuracy which is supported by other external factors of an individual. There is also a lack of a go-to reliable framework to increase ease of use. As of now, this method of detection is seemingly more tedious than traditional methods.

3 Methodology

To address some of the mentioned issues, we propose a methodology which follows a cumulative analysis approach. An approach that embodies various aspects of behavioral and characteristic changes a person portrays during depression, along with the results from the sentiment analysis.The two main observable behavioral changes a person shows are the changes in the sleep pattern [18–20] and changes in their physical activities on a day to day basis.

During depression, people often suffer from various sleep abnormalities like insomnia and hyper insomnia [21–23]. Data from researches show that the majority of the population reported sleep difficulties during depression [24]. Sleep controls of depressed people are often impaired, the period of wakefulness is high, reducing sleep efficiency [25]. This can be identified using REM(rapid eye movements). During sleep, eye movements are higher during a disturbed sleep [26, 27].

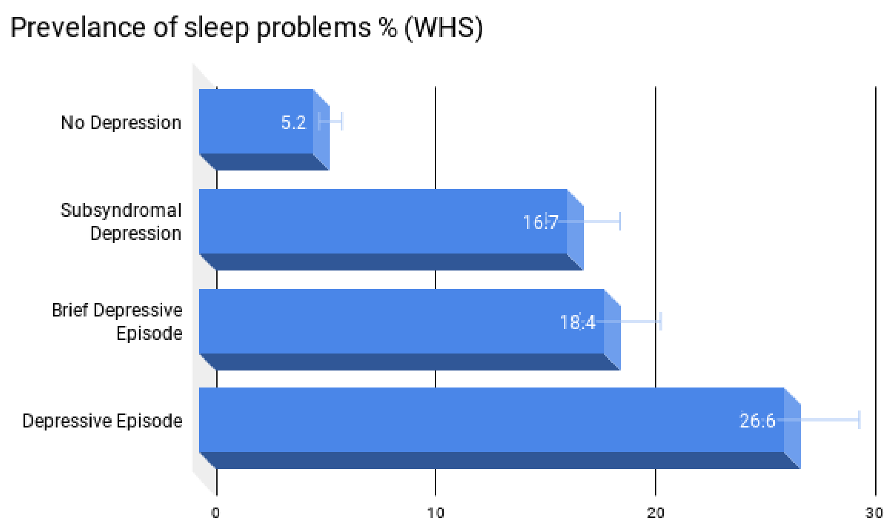

Fig. 2. Prevalence of sleep problems by different types of depression (95 percent confidence level) [28]

Depression leads to loss of appetite and loss of interest to perform any activity, this is a data point that helps us gain an association between physical activities taking place in different contexts and the symptoms of depression. Research shows that the symptoms of depression were lower in physically active people [29]. A cumulative analysis is an approach that combines all these factors to provide greater accuracy.

3.1 Cumulative Analysis

1. Crowd-sourcing of data and mental health survey: Twitter data, details of sleep patterns, physical activities, and caloric intake was obtained from the control group. A survey is then conducted on these people in order to determine a diagnosis of depression in the test subjects. The obtained values are then used to correlate and verify the results derived from the classification algorithm.

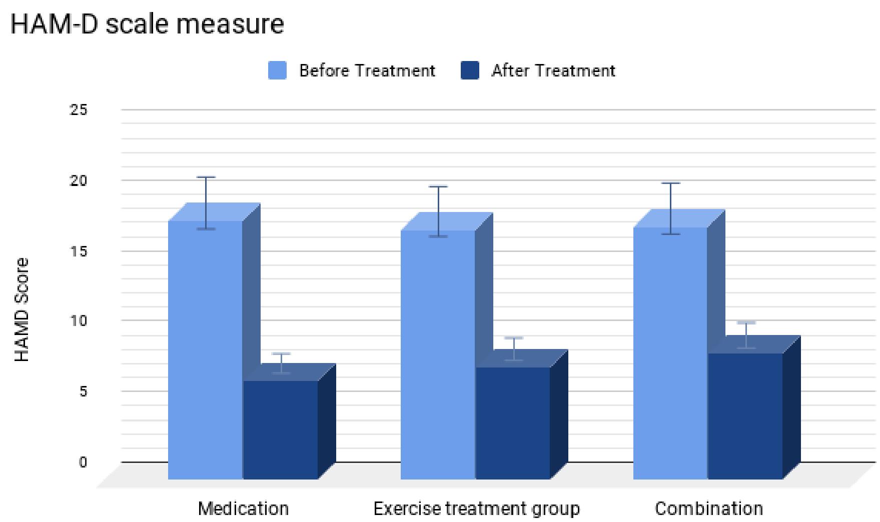

Fig. 3. Observed mean Hamilton Rating Scale for Depression before and after treatment [30]

2. Data from micro-blogging platforms: Crowd-sourcing is performed and text data is obtained from a group of people. This can be done from any social media platform where the user expresses his or her feelings using words.
3. Data of sleep patterns: Sleep cycle and quality of sleep are measured in the people that are a part of the crowd-sourcing. This data is obtained using simple sensors in one's mobile, these sensors determine the movement during sleep, using this the quality of sleep is measured.
4. Data of physical activities: Physical activities of the individuals participating in the crowd-sourcing is obtained. Low power location services and the motion sensors on one's phone detect activity types for outdoor activity and measure the intensity of an indoor activity. Based on that minutes moved by an individual is calculated and calories burnt throughout the day are estimated.
5. Data of caloric intake: The caloric values of each meal consumed by the subjects were recorded and aggregated in order to ascertain the total caloric intake. The average caloric intake was then derived from the total calories consumed by the subject group over the period of observation. This data can be recorded and submitted by the subject through self-documentation.
6. Classification algorithm: The sleep patterns obtained from the sensors of people participating in crowd-sourcing are compared with the sleep patterns of people that are not going through any mental illness in several different age group categories. An algorithm is deployed to map this variation for a prolonged period since a variation caused just for a few days may be due to

other external factors. The same method is used to determine deviation in the physical activities and caloric intake of an individual.

7. Cumulative analysis result: The result is derived from the sentiment analysis of the twitter data in conjunction with the physiological data obtained through crowd-sourcing. The classification algorithm is then trained on this amalgamated data (social media activities, sleep, caloric intake, and physical activities) to produce a prediction of depression diagnosis in the subject. Since the result obtained factors in a lot of other features, it produces a higher accuracy.

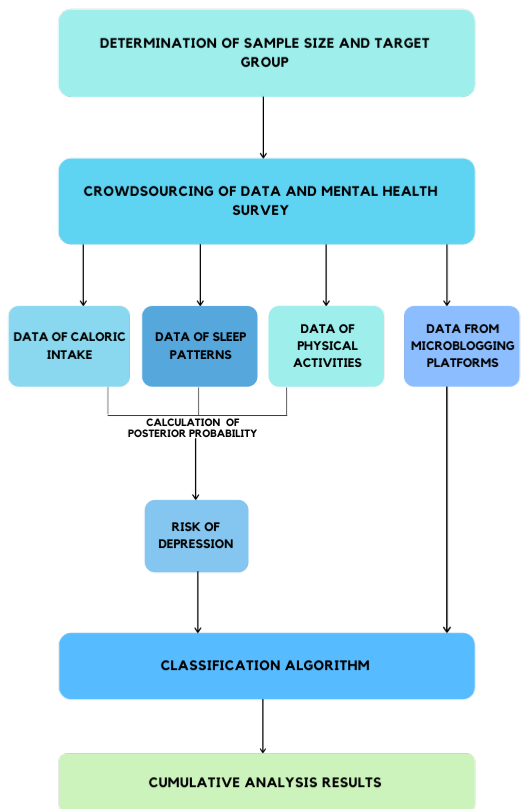

Fig. 4. Flowchart of proposed cumulative analysis.

3.2 Mathematical Model

The approach taken presents a system that identifies users at the risk of depression and is done on the basis of the text comprising their tweets and their associated physiological data such as food habits (caloric intake per day) and sleep pattern (hours of sleep per day). The algorithm used for this is based on the Multinomial Naive Bayes method.

A Naive Bayes classifier is a fairly simple, yet accurate mathematical model that is based on the Bayes Theorem of Probability in statistics. It is fairly on par in terms of accuracy and precision with classification algorithms such as Support Vector Machines, Logistic Regression, and others [31]. It operates under certain presuppositions such as each feature being independent of another, in essence, probabilities of occurrence of each event (in this case, words) are mutually exclusive and have no relation to the other. This greatly simplifies the computational complexity of the algorithm for a given body of the text.

Under the independence assumption of the Naive Bayes algorithm, each word in the tweet that is being analyzed is treated independently. The assumption is that the effect of the value of a predictor(x) on a given class(c) is independent of the values of other predictors, which is known as class conditional independence. Equation(1) shows the calculation of the value of posterior probability P(c—x) from P(c), P(x), and P(x—c), where P(c—x) is the posterior probability of class (target) given predictor (attribute), P(c) is the prior probability of class, P(x—c) is the likelihood which is the probability of predictor given class and P(x) is the prior probability of predictor. [32]

$$P(c|x) = \frac{P(x|c)P(c)}{P(x)} \tag{1}$$

Equations (2) and (3) detail the Naive Bayes algorithm [17], while equation (4) details the working equation of the Multinomial approach.

$$P(c_k|x) = \frac{P(x|c_k)P(c_k)}{P(x)} \tag{2}$$

$$P(c_k|x_1, ..., x_n) = \frac{1}{Z} P(c_k) \prod_{i=1}^{n} P(x_i|c_k) \tag{3}$$

The Multinomial approach of the Naive Bayes method lends to have a higher degree of accuracy resulting from the greater number of variables or factors being considered. An increase in the number of variables in a multinomial distribution leads to an increase in the bias and decrease in the variance of the model used.

$$(x|c_k) = \frac{(\sum_i x_i)!}{\prod_i x_i!} \prod_i {P_{k_i}}^{x_i} \tag{4}$$

The posterior probability of a diagnosis of depression in a subject based on his or her sleep pattern is calculated by taking the standard deviation from the standard average sleep cycle for a healthy human being of 7-9 hours [33] and dividing it by the average number of hours of sleep of the entire test group. The calculation of the probability of depression based on food habits is also conducted in a similar manner with the standard caloric intake being set at 2000-2500 calories per day [34]. The posterior probability of depression based on physical exercise is calculated with the standard exercise time for an adult being estimated at 150-300 minutes of moderate aerobic exercise per week(caloric depletion of 260-600 calories per 30 minutes) [35].

4 Conclusion

The paper thoroughly reviews popular methods of sentiment analysis that are performed on social media data to determine depression amongst users based on their social media posts. The paper also suggests a more holistic method of performing sentiment analysis on social media that factors in additional data primarily of which are sleep patterns and physical activities. This additional information allows us to obtain a more accurate measure of depressed users thus reducing the probability of misclassification. It also mitigates the effects of misclassification due to the inability to measure context or humor in social media posts, allowing for more useful data to be derived.

One of the implications of performing this method is that the data that is required to make the determination is not available for the general users on social media. The data has to be voluntarily documented and submitted by the user in order to conduct analysis through this method. This negates the ability to perform large scale analysis on social media platforms.

Another effect of using this method is that the results obtained are skewed towards the geographic area in which the user resides. This can heavily affect the extent to which the classification is aligned towards either end of the sentiment spectrum.

Further improvement in the accuracy of this method can be done by taking into consideration more factors such as dietary habits comprising a more detailed report of the dietary composition, in-depth recorded observations of the sleep patterns, and pre-existing health conditions. This would help in achieving a more accurate classification result of the user depression metrics as it improves the multivariate analysis result obtained.

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