Multilevel Predictor Model for Detecting Depressed Posts in Social Media

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Abstract - *The society is now facing an unexpected growth in the matter of mental disorders, with an estimated 300 million people suffering from depression all over the world. People with high life satisfaction usually do not suffer mental health issues at a higher level. Generation of data on social network platforms enables us to detect hidden patterns in data which are useful in obtaining meaningful insights. This work aims to (a) explore the relationship between life satisfaction and depression in social network users, using Twitter as an example, and (b) develop a multilevel predictive model to detect posts which convey a sign of depression using positive, negative and neutral as the three values . We trained a set of predictive models on datasets obtained by using a dictionary which carries the values for emotions and a survey called Centre for Epidemiological Study Depression (CES-D) scale. The resulting multilevel model establishes a negative correlation between life satisfaction and depression, and it can also display the accuracy of a predictive model using confusion matrix.*

Key Words: **Predictive model, Machine learning, Mental health, Depression, Life satisfaction, Social media, Confusion matrix.**

1. INTRODUCTION

Mental health is and continues to be a prominent invasion for the world. It is estimated that 300 million people are suffering from depression all over the world. . Depression is associated with being inactive and overthinking leading to major depressive disorder. Major Depressive Disorder is commonly referred to as clinical depression.

The probability for an individual to encounter a major depressive episode within a duration of one year is 3 – 5% for males and 8 – 10% for females. Yet, these effects of depression reach further than simply societal well-being. Depression affects workdays, diminishing work habits, and potentially inciting complications with concentration, memory, and decision-making behaviors.

This also stems further than simply the economic sphere, and often co-occurs with other illnesses and mental conditions. One in four cancer patients experience depression, one in three heart attack survivors undergo depression, and up to 75% of individuals diagnosed with an eating disorder will encounter the disease . Untreated depression increases the chance of dangerous behaviors. The significant challenge of detecting depression is the recognition that depressive symptoms may differ from patients' behavior and personality While these factors may be seemingly random on their own, they often coalesce into an undue burden on an ailing patient, thus vastly degrading the quality of life for an individual and their peers.

1.1 MDD - Major Depressive Disorder

The suicide rate exponentially increases as an individual suffering through one or more of these mental illnesses will likely experience a snowball effect towards others. Suicide itself is the cause leading to death. Clearly, depression has the potential to manifest itself within a cornucopia of other social issues, and therefore becomes a problem of high priority for our society to solve.

Effort to gain anti-depressants, or otherwise mask one's depression from a friend or family member. Furthermore, these questionnaires are often costly, and further it economically becomes a burden of receiving treatment for depression significantly.

Yet, before even examining flaws with the current methods of treating depression, one must simply be identified with the illness: the World Health Organization reports that the huge majority of depressed individuals never seek out treatment. This is particularly a trouble for the younger generation, which commonly will resort to blame and stifled self-esteem before seeking any sort of help. Even during visits with a primary health care physician, depression often goes unrecognized, and therefore undiagnosed.

Yet, when Major Depressive Disorder (MDD) is properly identified, contained, and treated, it may have far-reaching impacts upon society. Up to 80% of those treated for depression showed an improvement in their symptoms within a period of four to six weeks [10], thus bettering their lives, productivity, and boosting the economic status. A study funded by the National Institute of Mental Health developed a test to determine the effectiveness of depression treatment. Known as the Sequenced Treatment Alternatives to Relieve Depression (STAR*D): it reported depression remission rates of over 65 percent after probably six months of treatment. Therefore, it has become patently obvious that our wide contribution to combating clinical depression in certain countries would lie within improving techniques to identify Major Depressive Disorder, rather than in its treatment methods.

1.2 Treatment Methods

The most popular of these are the Center of Epidemiologic Studies Depression Scale (CES-D) , Beck's Depression Scale (BDI) , and Zung's Self-Rating Depression Scale (SDS) . Results on these examinations are determined from the patient themselves, or a third-party observation, but never from empirical data. Thus, these questionnaires often lend themselves flaws though subjective human testing, and may be easily manipulated to achieve a pre-determined prognosis.

People increasingly utilize social network platforms to share their innermost thoughts, desires, and voice their opinion on social matters. Postings on these sites are made in a naturalistic manner, and therefore provides a solution to the manipulation which self-reported depression questionnaires often encounter. We have concluded that social media provides a means to capture an individuals present state of mind, and is even effective at representing feelings of worthlessness, guilt, helplessness, and the levels of self-hatred that would often characterize clinical depression. We pursue the hypothesis that social media, through word vectorization, may be utilized to construct statistical models to detect and even predict Major Depressive Disorder, and possibly even compliment and extend traditional approaches to depression diagnosis.

2. METHODS

Twitter has become one of the most popular social media platforms since it launched, it advises 313 million active users who produce 6,000 tweets on Twitter every second as June, 2016. In favour of gathering the depression related data, we keep monitoring each streaming tweet that includes the word "depression" in entire Twitter platform [1]. Totally, we roughly have gathered large number of tweets that discussed the fields relevant to depression. Starting to web scraping the initial webpage, thousands of professional mental health tweets as well have been accumulated at the end.
A dataset can be developed from an amalgamation of users with public Twitter accounts who posted a status update in the form of a statement of diagnosis, such as "I was diagnosed with X today", where X would represent either depression or PTSD.

2.1 Data Collection

Create a twitter developers account and specify in brief the intent of the cause to work on sentimental analysis.Once approved, from that account you would need 4 things.The first one being "consumer_key = '', "consumer_secret = '', "access_token = '', "access_secret = ''

Create a file and insert the credentials so that you can download current tweets using keywords such as depression, anxiety or sadness. When data sets are ready you may proceed on the preprocessing stage.

2.2 Data Preprocessing

Because the data we have collected from the tweets are biased and noisy, making sure that the data is free of such noise is our first task. Generally, the special characters, such as retweet tags "@RT: xxx" and link address "http://www.", contain less information, they are removed at the beginning. In the next step, stop words and punctuations are removed by stop word list that has been extracted online. Non- words are very common in social media data due to any types of typo or acronyms, for instance, "hrt", "lmao". These words are filtered by the NLTK toolkit available in the python libraries. Basically the preprocessing stage will go through your data sets and the given dictionary. The dictionary essentially contains words with their corresponding polarity, which is helpful in calculating the sentiment of each tweet, each word will be filtered, tokenized and given its polarity. Every tweet will consist of the summation of all the polarity of each word which is basically divided by the number of words in that particular tweet. Finally, we had the raw data cleaned. Table 1 shows the number of words have left after each step of data preprocessing procedure.

2.2.1 Word Frequency

The primary use of the standard online dictionary available basically involves word frequency which is the basic approach to analyze data as to calculate the word frequency in the documents or otherwise called the text files. In the traditional text mining research, the frequent words are considered as the important words in the natural language processing. The collected data includes many common words that are semantically related to the depressive symptoms that we are familiar with, e.g. words "anxiety" and "disorder" are universal in the data set.

2.2.2 Data Analysis

Once preprocessing is done, you can find the file in the directory. Opening it you will find that the ID (Twitter User or tweet) and Sentiment of each tweet is segregated into 2 columns. With this output you now have a twitter data set and its corresponding sentiment filtered by depress keywords. (Positive, Neutral and Negative) as per the dictionary that contains words with their respective polarity. Each word taken from the tweet is compared with the dictionary and given a score. The sum of polarity is added for each tweet and if it is above 0, then it is a positive tweet. If it is equal to 0 it is neutral and if lesser than 0 it is a negative tweet. By this way tweets are classified as positive or negative.

2.2.3 Training

For training and predicting purposes we need to make sure that all the files are located in proper folders, the code written for analysis will run through the output.xlsx file which is the file that basically generates the ID and sentiment associated with it simultaneously recovering the tweet corresponding to the id of each sentiment. Using this we use the original data and feed them to our classifiers which is defined in the next step.

2.2.4 Classifiers

We employ four different types of binary classifiers in order to estimate the likelihood of depression within users. For each classifier, we utilize Scikit-Learn to implement the learning algorithms. We chose to evaluate Linear, Non-Linear, and Tree-based approaches in order to explore foundational learning models against our dataset. Ultimately, we decided upon Decision Trees, a Linear Support Vector Classifier, , as well as a Naïve Bayes algorithm. In this section, we attempt to explain how these algorithms work, as well as our implementation of them.

3. RESULTS

As per the understanding of the working algorithms a result depicting Postive means that the person is unlikely to have depression or anxiety. Neutral is the middle level wherein the user may or may not have depression but may also be more prone to being depressed. At this stage the user may display some depression like symptoms. Lastly, Negative is the lowest level where depression and anxiety symptoms are being detected through the users tweets. The more negative words the user uses means the more negative emotion the tweet carries. We also discuss the degree of accuracy to which the presence of active depression within a body of text may be ascertained from the analysis conducted. Classifiers were constructed by Machine Learning as detailed in for estimating the presence of signs of depression.

```
Tanushas-MacBook-Pro:Final tanusha$ python3 Accuracy_checker.py


Naive Bayes  Accuracy :
 92.94325512222976 %
 Completion Speed 0.53188

Decision tree Accuracy :
 98.38705245499652 %
 Completion Speed 2.35458
```

We utilize accuracy to denote each classifier's accuracy. We also obtain the performance of each classifier in the form of confusion matrix on a set of test data for which the true values are known. This is the key to the confusion matrix also known as an error matrix, is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one

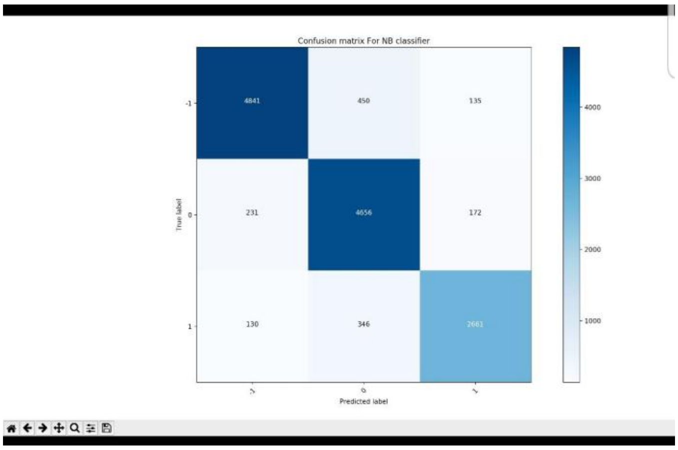

Table shows the accuracy as to which our constructed classifiers were able to discern the class of a small body of text. The classification accuracies are the average values which were used to vectorize the tweet. The result involves typing in a sample tweet, the tweet will go through the list of classifiers to predict the sentiment of the tweet you wrote and give the result as positive, negative or neutral. The algorithms were run on the test set and were able to give an accuracy in predicting positive and negative tweets.

```
Input your tweet :
i am good


*****************
Positive
*****************
```

4. CONCLUSIONS

Depression has been a serious mental illness since past decades which negatively affects human's health. It is difficult to confirm human's depression symptoms from their behaviors via restricted clinic records. Our proposed methods and experiments illustrate that social network provides rich and vast information for depression symptoms extraction from a distinctive perspective. We have demonstrated the potential of using twitter as a tool for measuring and predicting major depressive disorder in individuals. First, we compiled a dataset.Next, we proposed a Bag of Words approach towards quantifying this dataset creating a huge dimensional feature space as our input vector. Finally, we leveraged these distinguishing attributes to build, compare, and contrast several statistical classifiers which may predict the likelihood of depression within an individual.

The original data fed to our classifiers displayed all the AUC of each classifier .The ability to type in a sample tweet, The tweet will go through the highest AUC in the list of classifier to predict the sentiment of the tweet you wrote was also enabled. **Positive** result means that the person is unlikely to have depression or anxiety. **Neutral** means the middle level wherein the user may or may not have depression but may also be more prone to being depress. At that stage the user may display some depression like symptoms. Lastly, **Negative** is the lowest level where depression and anxiety symptoms are being detected through the user's tweets. The more negative words the user uses mean the more negative emotion the tweet has. Thus through these results depression level could be determined.

In the future, we will collect other types of data, e.g. image and video from other social networks. Additionally, advanced entity selection technique would be used to select more accurate and meaningful depression symptoms.

ACKNOWLEDGEMENT

This research paper would have been incomplete without the names of those people who have been constantly helping us achieve this milestone. I take this opportunity to express my deepest gratitude and appreciation to all those who have been the moral support helping me directly or indirectly towards the successful completion of this research paper.

I would like to express my gratitude to **Dr. C P S Prakash,** Principal, Dayananda Sagar College of engineering, DSCE, Bengaluru for this warm support throughout the course.

I am extremely thankful to **Dr. Ramesh Babu D R,** Vice Principal, and Head of the Department of Computer Science and Engineering, DSCE, Bengaluru for his motivation and encouragement and support.

For overall direction, I am very grateful to 8th semester coordinator **Dr. Vindhya P Malagi,** Assoc. Professor, Dept. of Computer Science and Engineering, DSCE, Bengaluru who has helped me by providing details relevant to this field helping us achieve the best of the outcomes required behind the completion of this paper.

I am grateful to Dept. of Computer Science and Engineering and Dayananda Sagar College of Engineering My sincere thanks to my guide, Prof. Prameetha Pai for imparting me the knowledge with which I could do my best. Finally, I Would like to thank all the staff members of Computer Science and Engineering Department, DSCE, and also other departments who are helping me directly or indirectly for the research regarding depression to be complete.

I sincerely thank my mentors, parents, family, and friends who have advised and pushed me forward throughout this endeavour. The product of this research paper would not be possible without all of them.

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