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Early Detection of Depression by Tweet Analysis

Tejashree Mahesh, Vasireddy Sathvika, Vimarsha R, Prakash C O
Department of Computer Science and Engineering
PES University
Bangalore, India

Abstract— *Depression is a psychological instability that isn't paid attention to in most parts of the world. Individuals never get treated to dysfunctional behavior instruction at school or at home. Many people have been determined to have depression and don't take medication to control it. They simply proceed with their lives without medications and their mental health deteriorates day by day.There are numerous encounters that can cause depression, such as losing a friend or family member, losing an employment, getting a separation and other predicament can lead an individual to feel blue, desolated and overpowered. Depression on social media - Social media stages are turning into an indispensable piece of individuals' lives. They mirror a user's very own life. By examining an individual's words, a reasonable and important window is made into their psychological side. The work is to build a model that can predict if the person is depressed or not based on the amount of trigger words used in their tweets. Even the slightest examination can give remarkable access into people's contemplations and sentiments and lead to considerably more prominent agreement and mental health treatment. The study of the effect of social media on depression in people of all ages, as well as the size of the connection between social media use and depression, may be a way for people to put out their problems and concerns and how to deal with it. For this study, a dataset has been created from scratch, examining tweets of over 50 Twitter users over a period of one month and this is used in the designed model to better understand and analyze the problem in hand. Vader sentiment-based analysis has been chosen to be applied here and the model is trained using LSTM + CNN. The model is written in Python and it tells if a given tweet is depressive or not.*

Keywords—*TWINT, VADER sentiment, LSTM, trigger words, depression*

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I. INTRODUCTION

Individuals like to share bliss, euphoria and trouble on social media. These stages are utilized for specialists to distinguish the reasons for depression and recognize it. Recognizing prior depression can be a tremendous advance to address the psychological instability and offer help to individuals experiencing mental illness.

By dissecting an individual's words, an unmistakable and important window is made into their psychological side.

Indeed, even the main examination can give remarkable access to people's contemplations and sentiments and cause significantly more prominent arrangement and treatment of their mental state.

The examination of the effect of online media on depression in users, and how huge is the relationship between web-based media use and depression, this could be the passage for individuals (particularly youthful grown-ups as well as teenagers) to put out their problems and concerns and how to deal with it.

The dataset has been created from scratch using the TWINT tool where tweets are scraped using keywords indicative of depression like 'depressive', 'lonely', 'suicide' etc., Over a period of one month, over 224750 tweets of 50 users have been scrapped. A dataset of random tweets has also been used to balance out the accuracy paradox of the imbalanced dataset.

In the wake of studying a few papers about utilizing diverse Machine Learning techniques to recognize depression on social media, VADER sentiment-based analysis has been chosen to be applied and the model is trained using LSTM + CNN. The model is written in Python and it tells if a given user is depressive or not by extracting his tweets and studying his tweeting behavior over a period of one month.

II. LITERATURE SURVEY

A. Detection of Depression-Related Posts in Reddit Social Media Forum [1]

Depression is a typical psychological well-being issue which is a sickness with a bunch of analytic measures. It is still under-analyzed and left with no treatment which can lead into a genuine self-discernment. It might as well lead to self-destruction and suicide. With the improvement of Internet use, individuals have begun to impart their encounters and difficulties to depression problems through online forms and tweets.

Making use of different Natural Language Processing (NLP) methods and techniques of classifying text, the authors of this paper tried to improve performance and accuracy. This paper centers around recognizing the presence of depression in Reddit Social Media Forum.

Depression language indicators had the words related to interruption with themselves, sensations of difficulty, strain, shock, aggression or self-harm contemplations, with a lot of prominent emphasis on the now and later. The results show that a higher accuracy is hidden in selection of proper features and combinations of multiple features. The viability of mixed features is demonstrated with the Multilayer Perceptron classifier arriving at 91% precision along with F1 score of 0.93 resulted in the best degree for depression identification in Reddit online media led in this study.

B. Anxious Depression Prediction in Real Time Social Data [II]

This dataset comprises the last one-month tweet entries of a hundred randomly selected users, scraped using the Twitter API. For the study, the first hundred followers of MS India's student forum on Twitter are taken into account.

The name, date of Twitter account formation, account verification status (verified or not), language of the tweet, tweet description, and tweet count are all included in each user's data. Each user's tweets, as well as the date and time of posting, the number of retweets, hashtags, and listed users, are retrieved.

The system architecture for the Anxious Depression Prediction model is as follows:

- The tweets collected over a period of one month for 100 users is passed through a feature extraction model.

- This feature extraction model splits the tweets into Lexicon words, Tweet timing, tweet frequency (how frequent does the user tweet), opinion contrast and negative optimism.

- These features are now passed into a feature matrix.

- This is now passed through an Ensemble Vote Classification model which in turn comprises a combination of Random Forest, Multinomial Naive Bayes and Boosting models.

- This way the model is able to predict if an input tweet while testing, is indicative of anxious depression or not.

The accuracies for the Multinomial Naive Bayes model are 77.89%, Random Forest is 81.04%, Gradient Boosting is 79.12% and Ensemble Vote as a whole is 85.09%.

C. Early Detection of Depression: Social Network Analysis and Random Forest Techniques [III]

Comments and posts were gathered from a social network and were considered as the input. Reddit, Inc data was obtained using Reddit, Inc’s API and the resulting dataset consisted of tuples in the form (id, writings), id is the unique key for every user on the social media network and writing is the comments or posts made by the user on the social media platform.

Within the subreddit of depression ‘depressed’ users are filtered out by searching for posts containing reports of diagnosed depression posted voluntarily by the users. Here, the date of diagnosis has been mentioned specifically. The absence of or error in the date of diagnosis does not affect the experiment as the intention was to detect if a user was ever in depression.

Posts were verified manually to check if they were genuine. At that point, an effect was made by haphazardly choosing an outsized arrangement of Redditors, no depression was analyzed with people who were dynamic on subreddit of depression. It was noted that taking part in the subreddit of depression does not imply the user is depressed. To say, people who are concerned and willing to help those are found to be in depression, reply and take part in this subreddit.

The features: semantic, writings and textual types were combined, and when the textual similarity metrics (cosine and BM25) made use of all textual fields, along with LSA (Latent Semantic Analysis) and WF (Writing Feature), the system gave results with best accuracies. When the same was done with normalized LSA, even though there was improvement in the results, it did not give a result that was better than the non-normalized LSA model.

D. Detecting the magnitude of depression in Twitter users using sentiment analysis [IV]

The users who had used a few keywords such as #addict, #abuse, #anxiety, #bullying and #addiction in their tweets in the form of tags were selected. These tags were used to make a list of users. The data was scraped from Twitter using Twitter API (Application Program Interface). 3200 tweets including retweets, videos etc. was considered. The data of 52 users each having around 2000 tweets has been considered. The data was segregated to different categories based on different days and time of the day to understand the variations for depression.
Taking the user "AADowd", it had been understood there had been several instances during which a negative value of depression had been observed for a substantial period.

It was clear that the user from day 32 to the day 44 had been under depression based on the negative values for a long sequence. When the tweets were analyzed, it was observed that the user was under depression, and hence the user seemed to be pointing out all negative things going around him these days and tweeting related to corruption in the politics, the lives being lost during war, the government not being able to help the families in need, the ill effects of war on the user's family, etc.

At this point, it had been clearly prominent that the user was mentally fixated at one point for an extended time period, which might have been a hospital or a house.
A difference in the tweets timing as compared to other period's tweets was observed therefore the tweets were consistent during this time and through certain hours of the day. The user was depressed from the 70th to the 84th day, and as a result, the user was either retweeting negative tweets by others or tweeting several negative tweets.

III. METHODOLOGY

The following are the steps involved in predicting signs of depression using text mining:

- Separating all tweets of 50 Twitter clients utilizing the watchwords 'discouragement', 'depressed' throughout some stretch of time by utilizing TWINT, a Twitter Intelligence Tool. Tweets over a range of one month since 2020 - 10-26 (YYYY-MM-DD design) were scraped.

- Keywords such as depression, depressed, anxious, sad, mental health, suicidal, etc. were used to scrape user specific tweets which are indicative of depression.

- Filtering out scraped tweets containing mentions and dummy values like '#NAME?' or just emojis or only https links.

- Scraped tweets which are in languages other than English are filtered out with the help of inbuilt functions in Microsoft Excel.

- Labelling of tweets in the dataset is done by assigning a sentiment value (+1 for positive, -1 for negative or 0 for neutral) to each of the tweets. Positive tweets imply that the individual is probably not depressed. Neutral implies that the client might or might not be depressed. It is the center level. Negative implies that the client is probably depressed.

- TextBlob is likewise a simple library that supports progressed examination and procedure on issue information. For vocabulary-based methodologies, a supposition is laid out by its semantic direction and accordingly the force of each word inside the sentence. These carve a pre-characterized wordbook grouping negative and positive words.

- To accomplish the assignment of marking the tweets in the dataset, TextBlob module of python is utilized. A tweet is resolved as a positive one if its relating extremity is more noteworthy than anything. In like manner, assuming the extremity of a tweet is 0, it is unbiased and in the event that if the extremity of a tweet is under nothing, the tweet is viewed as negative.

- Data pre-processing is used to clean and organize unstructured data into an understandable format. Pre-processing the data is done by removing stop words such as "the", "a", "an", "in" and tokenizing the tweets by splitting a tweet into a list of tokens. At the end of this, a labelled and pre - processed dataset in csv format is obtained.

- Expansion of contractions, removing joins, hashtags, capitalization, and accentuation, unsettle invalidation. removing connections and URLs along with whitespaces and stop words. For sure, stop words on the far side the quality NLTK stop words ought to be taken out to frame the model a ton strong, along with days of the week and months.
- Two kinds of tweets were considered: -
  - Random tweets which may or not may indicate depression.

- Tweets indicative of depression and/or symptoms of depression.
- A dataset of random tweets is sourced from the Sentiment140 dataset accessible on Kaggle. It contains 1,600,000 tweets removed through exploitation of the Twitter programming interface. The tweets are classified (0 = negative, a couple of = unbiased, four = positive) and that they might be acquainted with sight assessment.
- The scraped tweets are cleaned and processed. Expand withdrawals, remove joins, hashtags, capitalization, and accentuation, upset nullification. remove connections and URLs along with whitespaces and stop words.
- Pre-processing is done by removing hashtags, removing extra white spaces, expanding contractions, removing punctuations, removing image URLs, removing @mentions, emojis, stop words, tokenizing, stemming etc.
- Words specific and related to depression are used to collect the tweets, specifically to lexical terms as identified in the unigram. VADER Sentiment Analysis technique is adopted to achieve sentiment analysis.
- VADER sentiment analysis (well, within the Python implementation anyway) returns a sentiment score within the vary -1 to one, from most negative to most positive.
- The sentiment score of a sentence is calculated by summating the sentiment voluminous every VADER-dictionary-listed word within the sentence.
- Cleaning tweets is done using the following methods: 1. Check tweet length, save those > 6 (length of word "lonely"), remove hashtags, @mention, emoji and image URLs, Remove HTML special entities (e.g., &), Convert @username to AT_USER, expand contraction, remove punctuation, removing single space remaining at the front of the tweets, stemming words, removing stop words, etc.
- After cleaning the data, word cloud is created out of the cleaned Tweets to observe the difference between the 2 datasets. Word cloud of the Random Tweets and word cloud of Depressive Tweets were obtained.

- Data Visualization for depressive and standard posts is done using word clouds. Extracting meaningful insights from the word clouds is the key.

- Applying the preprocessing clean_text function to every element in the depressive tweets and random tweets data.

- A Tokenizer is utilized for sifting non-successive words and furthermore to appoint files. Guide of each exceptional word is created by the tokenizer and a list doled out to it. The model does the transformation of word to vector to sum up words for the forecasts.

- Word to vector and embedding matrices were utilized as a component of foreseeing depression. The embedding grid is a n x m lattice where n is the quantity of words and m is the element of the embedding. The base between the quantity of novel words is taken in the tokenizer and max words (in the event that there are less one-of-a-kind words than the maximum determined).

- Splitting and labelling the data is done. Assigning labels to the depressive tweets and random tweets data, and splitting the arrays into test (60%), validation (20%), and training data (20%). Combine depressive tweets and random tweets arrays and shuffle.

- This process involved assigning labels to depressive tweets and random tweets data. Splitting of dataset into training, validation and testing phases, combining depressive tweets and standard tweets arrays and shuffling is done.

- Model was assembled utilizing LSTM (Long momentary memory) and CNN. The model takes in an info and afterward yields a solitary number addressing the likelihood that the tweet demonstrates melancholy. The model takes in each info sentence, supplants it with its embeddings, and afterward runs the new installing vector through a convolutional layer. CNNs are appropriate for taking in spatial design from information. The convolutional layer exploits this and takes in structure from the sequential information which it passes into a standard LSTM layer. The yield of the LSTM layer is taken care of into a Dense model for expectation.

- The benchmark model chosen was a logistic regression model. Calculated regression examination is utilized to look at the relationship of autonomous variable(s) with one dichotomous dependent variable. This is as opposed to direct regression investigation in which the dependent variable is a continuous one.

- To assess the effectiveness of the LSTM + CNN model, a calculated regression model is prepared with a similar train information and a similar number of ages, and tried with a similar test information.

- Comparing the model with the benchmark model (logistic regression here) by creating a class to represent the logistic regression model, preventing overflow of exp by capping the activation and computing logistic regression coefficients using stochastic gradient descent.

- Then, the percent of total testing data is computed that is classified correctly and a number between 0 and 1 is returned as accuracy.

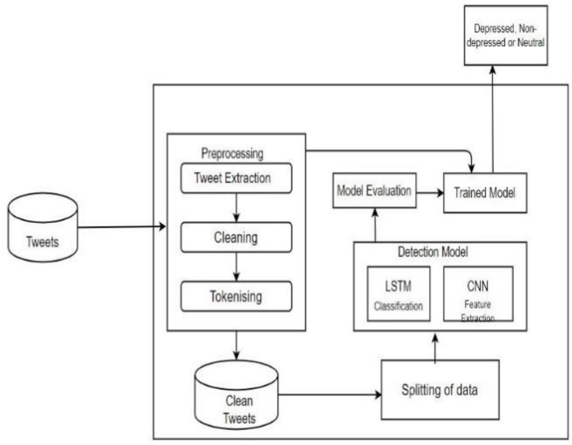

Figure 1: Low Level Design Diagram

➢ ***Data Collection***

∗ *Extracting tweets by scraping using the TWINT tool*

The collection of tweets for this project is biased as it is scraped with the keyword 'depression', from Twitter using the TWINT tool (Twitter Intelligence Tool).
TWINT is a scraping tool written in python used on Twitter for scraping Tweets from the profiles on Twitter without using Twitter's API, which means no authentication and no APIs needed whatsoever. This scraping with the TWINT tool yields two types of tweets: random tweets that don't signify depression and tweets that say the user might be depressed. Since there is no publicly accessible dataset of suicidal tweets, finding reliable tweets that are reflective of depression is extremely difficult. As a result, for this project, tweets that could be indicative of depression were collected using the Twitter scraping tool TWINT and the keyword "depression" by scraping all of 50 users' tweets over a one-month period starting on October 26, 2020. (YYYY-MM-DD format).
It's possible that some of the scraped tweets don't necessarily indicate that the user is depressed, like tweets linking to other articles about depression or tweets that promote a healthy mental condition. As a result, the scraped tweets are manually scanned once for better understanding the results.
A csv file of all the scraped tweets is obtained for each of the 50 users which is then merged into one common csv file which contains the tweets for all 50 users at one place (user-wise). To get a csv file of users whose tweets might or might not be depressive, tweets are scraped with the help of TWINT tool using the keyword 'depression' by typing in the code below:

twint -s depression -o filename.csv --csv

This doesn't include retweets but includes all replies and mentions. To now get all the tweets of the said users over a span of one month into a csv file, this code snippet was used:
twint -u username --since 2020-10-26 -o filename.csv --csv
(The date in this code should be changed accordingly to get tweets over a span of one month up to the current date.)

∗ *Cleaning the scraped Tweets*

Upon manually eyeballing the csv file it was found that many tweets contain mentions and dummy values like '#NAME?' or just emojis or only https links. These were filtered out using inbuilt Excel features.
Next, it was found that many tweets were not in English (the scope of the project includes working with tweets, tweeted only in the English language), these were again removed by applying a filter on the language column of the dataset to remove tweets that are in Spanish, Arabic, Indonesian etc.

➢ ***Labelling the dataset***

∗ *TextBlob approach*

The tweets in the dataset must each be labelled as positive, negative or neutral by assigning each tweet a sentiment value. To achieve this, the TextBlob module of python was used. Two new columns, Subjectivity and Polarity were created for the csv file. Subjectivity tells how subjective or opinionated the tweet is: A score of 0 may be a fact and score of 1 is an opinion. Polarity tells how positive or negative a tweet is with +1 being the highest positive score and -1 being the highest negative score. Next, based on the Polarity scores the tweets were analyzed to label them as positive, negative or neutral. Words specific and related to depression were used to collect the tweets, specifically to lexical terms as identified in the unigram.

∗ *VADER approach*

VADER Sentiment Analysis technique was adopted to achieve sentiment analysis. VADER sentiment analysis (well, within the Python implementation anyway) returns a sentiment score within the vary -1 to one, from most negative to most positive. The sentiment score of a sentence is calculated by summation the sentiment voluminous every VADER-dictionary-listed word within the sentence.

➢ ***Preprocessing the dataset***

∗ *Tokenizing the Tweets*

A token is a piece of a whole thing, so a word can be a token in a sentence, and a sentence can be a token in a paragraph. In tokenization a string is split into a list of tokens.

import nltk
from nltk.tokenize import word_tokenize

∗ *Removing stop words from the Tweets*

A stop word is a widely used word that a search engine has been instructed to ignore when indexing and retrieving entries as a result of a search query. The *nltk* module of python which has a default list of stop words in the English language is used for this.

import nltk from nltk.corpus import stopwords

➢ ***Finalizing the dataset***

For ease of passing, it into the model and performing computations on it by training it using various ML algorithms, currently, only the tweet id and tweet sentiments (+1, 0, -1) have been extracted into another csv file and this is passed as input, into the model.

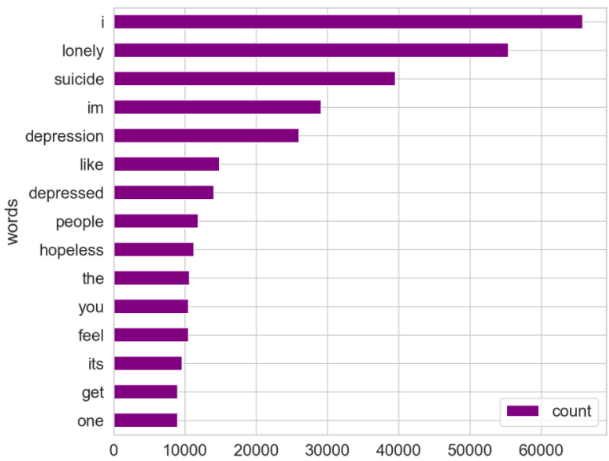

Figure 2: Common words found in Tweets (including all words)

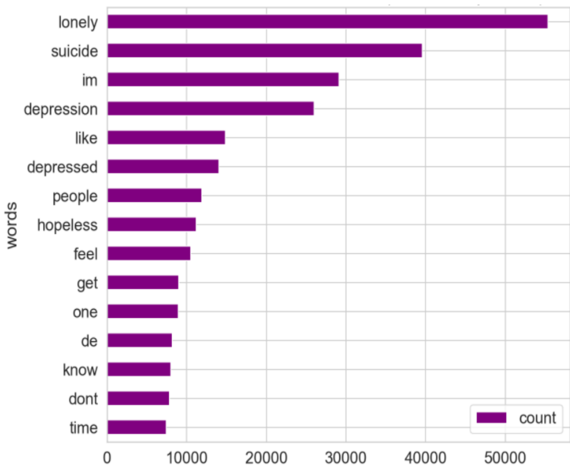

Figure 3: Common words found in Tweets (without stopwords)

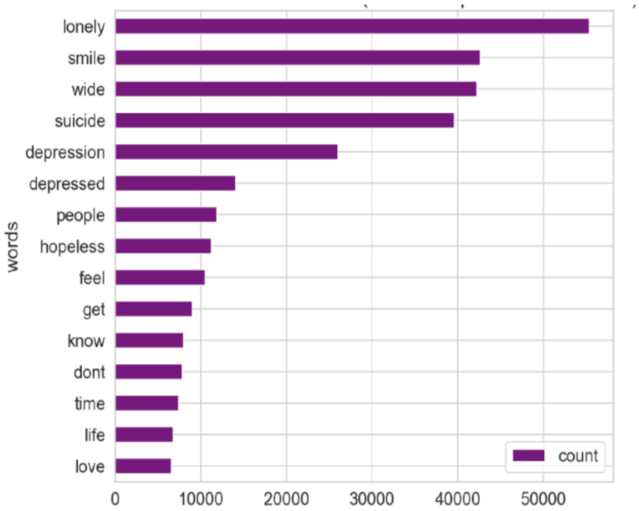

Figure 4: Common words found in Tweets (without stopwords and collection words)

Result: Dataset with 224250 tweets of 50 users over a span of one month, along with tweet id, name, date and time of tweet, time zone, username, user id, tweet, language of tweet, retweets count, replies count and likes count as the columns is created from scratch.

Although accuracy is a reasonable starting point for assessing a model, this one has an unbalanced dataset, necessitating the use of additional metrics to evaluate its robustness, accuracy and loss. The accuracy score in an imbalanced data model is likely to be high, but the underlying class distribution can only be represented by the accuracy score. The name of this situation is the accuracy paradox. This is because the model learns to always predict the most popular class, which is frequently the right class to predict. It was necessary to gather a greater amount of data and adjust the output metric to consider other factors also along with the accuracy score because of the paradox of accuracy.

It was simple to see the differences between the two datasets after cleaning the Tweets by building a word cloud.

V. MODEL EVALUATION AND VALIDATION

The tokenized tweets are fed into the LSTM model which is in turn sent to the embedding layer to urge an embedding vector.

When an input tweet is given to the model, it outputs the probability of the tweet being indicative of depression.

The model replaces the Tweet given as inputs with its embeddings, the same is passed to the convolutional layer. Structure of the sequential data is learnt by the convolutional layer, and then sent to the LSTM layer.

This model is contrasted against the benchmark model (logistic regression). The calculated regression model is prepared with the named information, and the precision of the benchmark model is gotten and the test data is foreseen.

For prediction, the output from the same is passed into a dense model. The model has the following: -

1) embedding layer
2) convolutional layer
3) dense layer
4) max pooling is used with a dropout of 0.5 Nadam optimizer
6) binary cross-entropy loss
7) Relu activation function within the first layer
8) sigmoid activation function within the dense layer.

VI. RESULTS

The model's accuracy and loss are tracked and visualized, and the results are compared to the logistic regression model which is considered to be the benchmark.

This model has an accuracy of 96.67% and the benchmark model has an accuracy of 59.872%.

VII. CONCLUSIONS

Using linguistic markers as a tool for analyzing and diagnosing depression, has a lot of potential. Depression can be readily detected in the document without the use of complex models. Simply collecting, cleaning, and analyzing publicly available data can show the difference between random Tweets and Tweets with depressive characteristics.

It is impossible to overestimate the value of linguistic research in the field of mental health. One can get a good picture of a person's emotional state by analyzing his or her words. Even the most basic study of social media can give unparalleled access to people's thoughts and emotions, leading to significantly improved mental health awareness and care.

The final model outperforms the comparison model by a wide margin. The benchmark model has an accuracy of about 60% when run for the same number of epochs and on the same data, while the final model has an accuracy of about 97 percent. This model for depression prediction is much more robust and accurate, and it is evident that this method is close enough to have solved the complexity of effectively analyzing depression level in the tweets.

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