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Depression Detection Model Based on Sentiment Analysis on Twitter API

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Abstract— **Datasets derived from social networks are useful in a number of areas, including sociology and psychology. However, technical assistance is inadequate, and precise approaches are desperately needed. Our project uses data mining in the field of psychology to classify depressed consumers of twitter. To begin, a sentiment analysis approach is proposed that uses vocabulary and man-made rules to measure social media's tendency (twitter). Second, a depression identification model is developed using the proposed approach and ten depressed consumer characteristics derived from psychological studies. The model is then tested using three different forms of classifiers. The relevance of each function is also investigated. Finally, within the proposed model, a tool for online mental health monitoring is created. Some psychologists endorse this research, which helps them boost their data centric approach to analysing the impact of major events.**

Index Terms— **social media, API, data mining, classification, depression.**

I. Introduction

The proliferation of internet and communication technology, especially online social networks, has revitalized people's electronic interactions and communication. Applications like Twitter and others allow users to share their thoughts, emotions, and sentiments about a matter, subject, or problem online in addition to hosting written and multimedia material. On the one hand, this is great for members of social networking sites to publicly and honestly contribute and respond to any subject online; on the other hand, it allows health professionals to gain insight into what could be going on in the mind of someone who responded to a topic in a particular way.

To provide such insight, machine learning techniques could potentially offer some unique features that can assist in examining the unique patterns hidden in online communication and process them to reveal the mental state (such as 'happiness', 'sadness', 'anger', 'anxiety, depression) among twitter's users.

II. LITERATURE REVIEW

Various studies have been reported exploring the potential of social media to predict several forms of depression in social media users. The studies are being conducted on the data collected from Twitter (Choudhury et al., 2013a; Choudhury et al., 2013b; Resnik et al., 2015; Pedersen et al., 2015; Tsugawa et al., 2015; Reece et al., 2017; Coppersmith et al., 2014a; Coppersmith et al., 2014b; Nadeem et al., 2016; Wang et al., 2013; Kale, 2015; Park, 2013; Mowery et al., 2017), Facebook (Choudhury et al., 2013c; Schwartz et al., 2014), Reddit (Shen & Rudzicz, 2017), Instagram (Reece & Danforth, 2017) and web forums. In a study (Shen & Rudzicz, 2017) authors classified Reddit posts related to anxiety by applying N-gram language modeling, vector embeddings, topic analysis, and emotional norms to generate features. In a work (Choudhury et al., 2013a, Choudhury et al., 2013b) authors used crowdsourcing to collect data of Twitter users with clinical depression and measure behavioural attributes to build a classifier in order to identify depression in a person. In another study (Choudhury et al., 2013c) the authors used Facebook data and developed a series of statistical models to predict postpartum depression. Authors (Rensik et al., 2015) explored the use of supervised topic models in the analysis of linguistic signals for detecting depression in Twitter. Authors (Pedersen et al. 2015) used lexical features to train decision lists to identify Twitter users with depression. In another work (Tsugawa et al., 2015) authors extracted features from the activity history of users on Twitter for estimating the degree of depression. In a research (Schwartz et al. 2014) authors used survey responses and status updates from 28,749 Facebook users to develop a regression model that predicts users' degree of depression based on their Facebook status updates. Authors (Reece et al., 2017) extracted predictive features measuring effect, linguistic style, and context from Twitter data to build models with supervised learning algorithms in order to predict the emergence of depression and Post-Traumatic Stress Disorder in Twitter users.

In a study (Coppersmith et al., 2014a) authors presented a method to obtain a post-traumatic stress disorder classifier for social media using Twitter data demonstrating its utility by examining differences in language use between PTSD and random individuals. In another study (Coppersmith et al., 2014b) the authors analysed mental health phenomena in publicly available Twitter data by gathering data for a range of mental illnesses quickly and cheaply to detect post-traumatic stress disorder, depression, bipolar disorder, and seasonal affective disorder. Authors (Nadeem et al., 2016) used crowdsourcing to collect data of Twitter users with diagnosed depression. They used the Bag of words approach to quantify each tweet in order to leverage several

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statistical classifiers to provide estimates to the risk of depression. (Wang et al., 2013) proposed a depression detection model based on 10 features and 3 classifiers to verify the model on Twitter data.

They also developed an application based on their proposed model for mental health monitoring online. In another work (Reece & Danforth, 2017) authors applied machine learning tools to identify markers of depression on photos from Instagram. They used colour analysis, metadata components, and algorithmic face detection to extract statistical features from Instagram photos. The author (Kale, 2015) targeted Twitter data to identify users who could potentially suffer from mental disorders and classify them based on the intensity of linguistic usage and different behavioural features using sentiment analysis techniques. In a work (Park, 2013) authors concluded in their work that Non-depressed individuals perceived Twitter as an information consuming and sharing tool, while depressed individuals perceived it as a tool for social awareness and emotional interaction.

In a work (Mowery et al., 2017) authors conducted two feature study experiments in order to use the predictive power of supervised machine learning classifiers and study the influence of feature sets for classifying depression-related tweets. Recently deep learning techniques have also been used for depression detection on social media. Authors (Orabi et al., 2018) used deep neural networks on Twitter data for detection of depression among Twitter users. (Trotzek et al., 2018) compared their convolution neural network-based model on different word embeddings to a classification based on user-level linguistic metadata. Finally, an ensemble of both approaches is shown to achieve state-of-the-art results in a depression detection task

III. PROBLEMS AND PROPOSED SOLUTIONS

Psychological researchers and students looking to conduct studies on the impact of social media on depression find themselves having to manually go through thousands of user-generated messages to have a chance at understanding the mentality of the users and form theories from them.

The current system is highly inefficient and equally undependable as the biases that can occur between each student/ researcher can throw off the findings. The other commonly used method is to carry out surveys but the results of surveys can never truly paint an accurate picture due to unreliable reporting from the participants.

There are, therefore, many issues with the current system.

A. Problems:

Unreliable reporting: Since most of the surveys are broadcast over online channels, users tend to take them in an uncontrolled environment. This means there is no guarantee that the study group is taking care to answer each question carefully and even if they do, might be projecting a version of themselves that is inaccurate and can lead to errors in the study.

Time: The current system requires a lot of time to enter the data because the researchers have to go to each tweet and log them in. Apart from that, they have to make sure there are no errors made while logging in details.

Information Tampering: There are multiple points of data entry that increase the chances that errors can be made, intentionally or unintentionally while the data is being gathered.

Subjective Readings: Since each reading is carried out manually, the chances that there are different readings for a single tweet are substantially higher than with a machine-generated algorithm.

B. Proposed Solutions:

Online data collection: By collecting all the data straight from Twitter through its in-house API, we can eliminate the need to manually read through all the data.

Centralized Database: A centralized collection of all the readings of the tweets for future studies.

Unbiased Analysis: Since the new system is IT-based and all the information is processed on computers, we can analyse the tweets more consistently.

Overall, the new proposed system helps collect large amounts of data and insights. The proposed system will reduce the research time and redundancy significantly. The new system reduces the chances of inconsistencies. The system collects tweets and classifies the sentiments into three categories. It takes inputs from industry experts to improve the ml model to get better at recognizing the signs of depression, which will only get better as time passes.

IV. SYSTEM ANALYSIS

A. Functional Requirements

The functions of a system or its elements are defined by functional specifications. What a machine is meant to do is defined by functional specifications. A collection of inputs, outputs, and actions is referred to as a function. Calculations, technical details, data manipulation and retrieval, and other basic features that determine what a machine is intended to do are examples of functional requirements. Functional requirements specify the particular results of a system.

Functional requirements for our system**:**

- The system must be able to capture data in real-time.
- The system must be able to keep up with updates in the Twitter API.
- The system must be able to improve over time.
- The system must allow admins to make changes and improvements.
- The system must be able to classify the tweets into different categories.
- The system must generate a database of all the insights for future reference.

B. Non-Functional Requirements:

Non-functional specifications, rather than defining individual actions, define parameters that can be used to evaluate a system's operation. Non-functional specifications describe the behaviour of a machine. These are the features that don't do much but are crucial to the system's function. Style, user interface, user environment, compatibility, and so on.

Non-Functional requirements for our system:

- The system should have a low down-time.
- The system should allow admins to use different input methods.
- The system should be optimized for performance.
- The system should not crash under heavy load.

V. PROPOSED MODEL

The Proposed Depression Detection Model Anxious depression is a mental health concern where pre-diagnosis, which is an early screening of symptoms, may help signal to warn about the degree of disorder. The pervasive social web can provide an opposite test-bed for understanding user behaviour and mental health. This research proffers a predictive model to detect anxious depression in real-time tweets of users. The following figure 2 depicts the architecture of the proposed AD prediction model.

A. Data Collection

For each user, tweets are fetched, with the date and time of post, a number of re-tweets, hashtags, mentioned users.

B. Pre-processing:

It is the process of cleaning and filtering the data to make it suitable for feature extraction.

The process includes:

• Removing numeric and empty texts, URLs, mentions, hashtags, non-ASCII characters, stop-words, and punctuations.

C. Anxiety Lexicon Base:

Depressive rumination is the compulsive focus of attention on thoughts that cause feelings of sadness, anxiety, and distress. A person with anxious depression disorder is very likely to verbalize thoughts using specific anxiety-related words. Therefore, an anxiety lexicon base with a seed list of 60 words is built with keywords that represent anxious depression in the textual content.

Anxious depression-related words
Fat, bad, weak, problem, tired, illusion, restless, bored, crap, sad, escape, useless, meaningless, crying, reject, suffer, sleepless, never, bored, afraid, unhappy, ugly, upset, awful, torture, unsuccessful, helpless, suffer, fail, sorrow, nobody, blame, damaged, shatter. pathetic, insomnia, kill, panic, lonely, hate, depressed, frustrated, loser, suicidal, hurt, pain, disappoint, broke, abandon, worthless, regret, dissatisfied, lost, empty, destroyed, ruin, die, sick.

Table 1 presents the lexicon base of the initial 60 words.

Table 1-Lexicon for Anxiety Detection

VI. SYSTEM DESIGN

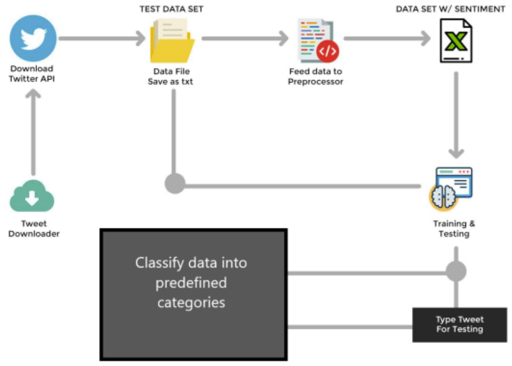

Fig. 1. Data Flow diagram showcasing the collection and subsequent processing of data following which it is classified

The system starts off by downloading tweets from the Twitter API.

These tweets are stored in a text file which is then fed to the pre-processor.

The data pre-processing will go through the data sets and the given dictionary. The dictionary contains words with their corresponding polarity, which is essential to calculating the sentiment of each tweet, each word will be separated, tokenized, and given its polarity. Every tweet will consist of the summation of all polarities of each word and divided by the number of words in that tweet.

Once pre-processing is done, each tweet is stored with its sentiment. This is the dataset and each tweet is categorized into 3 types: Positive, Negative, or Neutral. Positive, this means that person is unlikely to have depression or anxiety. Neutral, this is the middle level wherein the user may or may not have depression but may also be more prone to being depressed. 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 means the more negative emotion the tweet has.

In testing and training, the system will run through the dataset generated after pre-processing and at the same time recover the tweet corresponding to the type of each sentiment. Using this we use the original data and feed them to our classifiers.

The classifiers then predict the overall sentiment from the input provided by the user. The result can be used to draw insights into the overall mental health of Twitter users.

VII. METHODS

Using the same known data set to test accuracy, we trained and tested around 10,000 tweets and compared the running time and accuracy of the chosen classification algorithms.

We then chose the best combination of speed and accuracy and used a library that performed sentiment analysis using the chosen algorithm.

A. Naive Bayes

Naive Bayes classifiers are a collection of classification algorithms based on Bayes' Theorem. It is not a single algorithm but a family of algorithms where all of them share a common principle, i.e. every pair of features being classified is independent of each other.

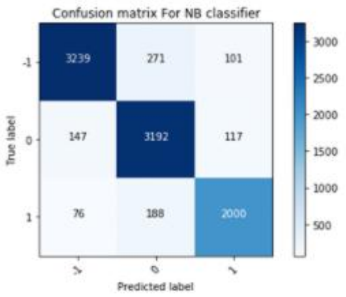

Fig. 2. Confusion Matrix showcasing the accuracy of the results of the Naive Bayes Algorithm against the known results

Accuracy:93.79406648429645%

Completion Time: 0.59779

B. k-nearest Neighbours

K-Nearest Neighbours (KNN) is one of the simplest algorithms used in Machine Learning for regression and classification problems. KNN algorithms use data and classify new data points based on similarity measures (e.g. distance function). Classification is done by a majority vote to its neighbours.

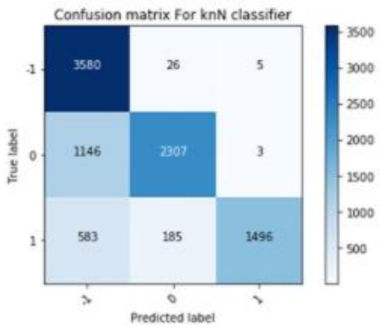

Fig. 3. Confusion Matrix showcasing the accuracy of the results of the knN Algorithm against the known results

Accuracy: 81.464022923447 %

Completion Time: 7.99048 Seconds

C. SVM

A support vector machine (SVM) is a machine learning algorithm that analyses data for classification and regression analysis. SVM is a supervised learning method that looks at data and sorts it into one of two categories.

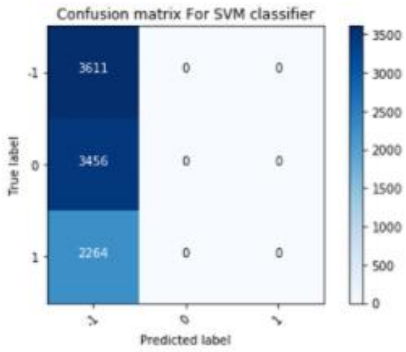

Fig. 4. Confusion Matrix showcasing the accuracy of the results of the SVM Algorithm against the known results

Accuracy: 50.0 %

Completion Time: 29.83311 Seconds

D. Random Forest

Random forest builds multiple decision trees and merges them together to get a more accurate and stable prediction. Random forest has nearly the same hyper parameters as a decision tree or a bagging

classifier.

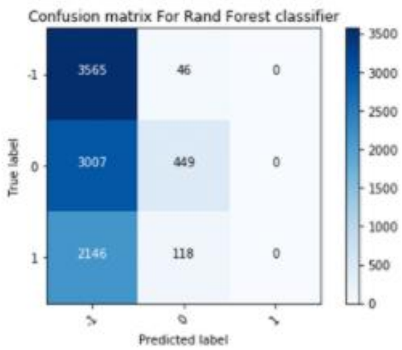

Fig. 5. Confusion Matrix showcasing the accuracy of the results of the Random Forest Algorithm against the known results

Accuracy: 49.1038137743686 %

Completion Time: 0.60994 Seconds

E. D tree

Decision trees use multiple algorithms to decide to split a node into two or more sub-nodes. The creation of sub-nodes increases the homogeneity of resultant sub-nodes.

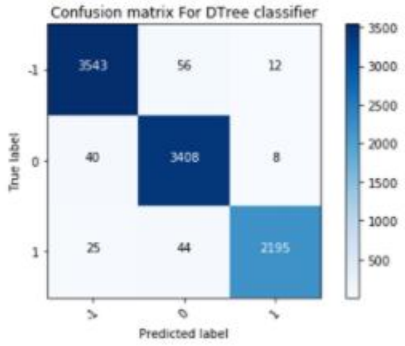

Fig. 6. Confusion Matrix showcasing the accuracy of the results of the D Tree Algorithm against the known results

Accuracy: 98.55668748040587 %

Completion Time: 3.40457 Seconds

F. Choosing a Library

After the tests have been run, it is clear that the most efficient and accurate algorithm we can use is Naive Bayes. The most used sentiment analysis library which uses the Naive Bayes algorithm for classification is the text blob library for python. Along with the tweepy library, we can collect, pre-process, and classify all the tweets from specific twitter handles based on specificity and polarity, which should give us a general idea of the mood/sentiment of the respective user, which we can then use to determine if they are exhibiting signs of depression.

VIII. RESULTS

	Tweet	Created	Subjectivity	Polarity
0	Since taking office, the Biden-Harris Administ...	2021-04-14 20:31:09	0.000	0.00
1	Nearly 10 million Americans are still unemploy...	2021-04-13 17:44:15	0.400	0.10
2	Every American who wants a job that pays fairl...	2021-04-12 20:54:46	0.375	0.35
3	No child should have to drink water poisoned b...	2021-04-11 21:29:47	0.000	0.00
4	Universal background checks are supported by t...	2021-04-09 18:17:33	0.500	0.00

Fig. 7. A sample output showing the subjectivity and polarity of each tweet of a given user

After the data has been pre-processed and run through the algorithm we end up with a table with the tweet and its respective subjectivity and polarity. Using this we determine if the overall mind-set of the user is positive, negative or neutral. A positive mind-set would indicate a lower chance of being depressed whereas a negative mind-set would indicate the opposite.

Once the website was implemented we are now able to provide an interface for the target audience to be able to use the interface without any technical know-how.

Fig 8. Our completed website processes the input user's handle; we ignore tweets that have a low subjectivity so as to avoid being overwhelmed by neutral readings that show no insights into the person's true feelings.

IX. CONCLUSION

Social networking has changed the way we communicate with the world, helping us to remain linked while still expressing ourselves. Anxiety, depression, and social media seem to be locked in a vicious circle, with one issue always triggering the other. In this study, tweets from Twitter users are analysed and a supervised learning-based prediction model is proposed. The presence of anxiety-related words was considered as linguistic markers whereas counting of negative tweets and polarity contrast of tweets related to semantic markers.

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