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AI-based Mental Health Diagnosis and Prognosis of Youth during COVID-19

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Abstract

The COVID-19 pandemic's global lockdown and physical isolation have a negative impact on youth mental health. The rise of social media around the globe enables individuals to express, self-reflect, and connect with peers. As a result, we extrapolate mental health and well-being trends in three ways: social media anxiety disorder, anxious depression social media verbalization, and social anxiety. Based on linguistic clues and user posting behaviors, we developed a predictive algorithm to detect mental health disorders in online real-time Twitter messages using supervised learning algorithms. We use three classifiers; Random Forest, Naïve Bayes, and AdaBoostM1.

1. Introduction

The novel COVID-19 pandemic has wreaked havoc on people's physical health, and the coronavirus is having a detrimental influence on our mental health [1]. Aside from tracking the transmission of disease, public health professionals are increasingly focused on tracking the emotional shifts that epidemics cause in the general populace.

Social media platforms allow members of the public to openly express and share their emotions with others. Data from social media may reveal a lot about a person's physical and mental health. Data may be collected and analyzed in real-time from social media platforms like Twitter, with the potential to poll public sentiment (opinion) on a specific topic [2].

Twitter is a social networking and microblogging app for mobile devices. There are around 955 million Twitter users who can send tweets containing text, video, pictures, or links to other websites. Twitter is used by one-third of those who have a social media profile, with 75 percent accessing it via a portable device to express their opinion [3]. Sentiment analysis has found its way into mainstream healthcare studies based on Twitter. Twitter is a popular platform because its application programming interface makes data collection simple.

Social scientists and psychologists are interested in a deeper understanding of human emotions, psychology, and mental health because of the extraordinary development of information available through social media [4]. In terms of patient-centered health care, Bates et al. have defined social media as a "perfect storm," which is a useful source of data for the public and health institutions [5].

Sentiment analysis examines the strength of positive and negative views and emotions expressed in free-text natural language (either words and/or symbols used in a communication). The text section of a tweet contains the tweeter's opinion. This is expressed in a free-text format, which is unstructured and non-standardized. Measuring the mood of a healthcare tweet accurately provides a chance to learn about both the patient's and healthcare professional's perspectives on a health topic [6]. Because depression is a very prevalent mental disease that impacts a variety of behaviors and communication patterns, it has emerged as the primary mental health condition of interest among computational social scientists [7]. Depression underdiagnosis is still an issue; a recent assessment of a major metropolitan region revealed that almost half (45%) of all instances of severe depression went untreated [8]. PTSD is commonly associated with severe depression, despite its rarity [9]. According to studies, the majority of primary care doctors underdiagnose or under-treat PTSD [10].

The consequences of the underdiagnosis of many diseases are significant, both in terms of human quality of life and healthcare systems. Early screening and diagnosis of depression and PTSD using computational approaches have the potential to have a beneficial influence on a major public health issue with little costs and human intervention.

Zhu et al. looked at how the Chinese public's mental state changed during the SARS pandemic in 2003 [11]. They discovered that 96.4 percent of those polled, experienced emotional changes and unpleasant feelings such as panic (54.8 percent), anxiety (34.0 percent), and dread during the epidemic (7.6 percent). Unpredictable conduct may result from psychological changes. 23.3 percent of those polled acknowledged engaging in "irrational" activities such as going on a shopping spree or taking measures such as seeking refuge, preparing food, and so on.

The rest of the paper is designed as follows: section 2 is related to literature about sentiment analysis and mental wellbeing. Section 3 covers the

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methodology used for mental health sentiment analysis. This is followed by discussion and results in section 4 and a conclusion in section 5.

2. Literature Review

There is increasing literature that applies advanced approaches for drawing informed judgments about Twitter users' mental health based on their online behavior. According to Kent et al [12], up to 40 percent of health care tweets contain some sort of sentiment. A validated technique for sentiment analysis of healthcare tweets on Twitter would allow for a large-scale evaluation of public opinion [13].

Twitter may be used to gauge the severity of depression. Machine learning was employed with around 69 percent accuracy [14]. Using characteristics like word frequency "bag of words", positive-to-negative word ratio, the number of words, tweets containing URLs, or first-person pronouns, it is possible to predict sadness with a decent level of accuracy.

Tweets of each person are recognized as having features that reflect their sentiment [15]. The emotional state, the timing of the message, the linguistic style, and the n-grams were all features of the post. This is consistent with what psychologists have said about people diagnosed with depression [16]. For example, the timing of postings might suggest sleep deprivation or being active at specific times of the day, whereas n-grams (mainly unigrams) can indicate a refusal to completely express words.

Early attempts to detect depression and post-traumatic stress disorder (PTSD) signs in Twitter data have yielded encouraging results. Park et al. discovered that depressed Twitter users were more likely to publish tweets with negative emotional sentiment than healthy users [17]. Based on changes in Twitter usage and tweet content, De Choudhury et al. effectively-identified new moms suffering from postpartum depression [18].

De Choudhury et al. discovered depressed signals in tweets posted by people suffering from Major Depressive Disorder in a different study [19]. De Choudhury et al. also discovered that increasing social isolation, as assessed by Facebook data, was associated with postpartum depression in mothers [20]. Few studies have tried to find PTSD indicators in Twitter data [21,22].

Reece et al. created computer models to predict the onset of depression in Twitter users with Post-Traumatic Stress Disorder [23]. To create models, they utilized supervised learning techniques using all these characteristics. Emerged models were better at distinguishing between individuals who uploaded healthy material and those who posted stuff that showed sadness.

Using a Lexicon-based method, Singh et al. presented an approach for evaluating feelings from social media comments [24]. The suggested method was primarily concerned with subjective data obtained from Facebook. The writers' main focus was on categorizing the comments as positive, negative, or neutral, which provided an accurate estimate of likes and dislikes for the postings.

Singh and Wang aim to identify depressed people from tweets, and they built their own dataset by collecting tweets from various Twitter pages and labeling them with the polarity score derived from the Python package Textblob [25]. The researchers then built several deep learning models, including RNN, CNN, and GRU, which were used to generate predictions on the dataset. For each model, they looked at the effects of character-based vs. word-based models, as well as pre-trained vs. learned embeddings.

Nadeem et al. investigated the capacity of social media to predict the onset of Major Depressive Disorder (MDD) among internet users [26]. They compiled a list of Twitter users who could be diagnosed with depression using a crowdsourcing technique. Also utilized the bag of words method on tweets gathered over the course of a year, then applied several statistical classifiers to estimate the probability of depression. The Naïve Bayes Algorithm, Decision Trees, and a Linear Vector Classifier were used.

Rosa et al. discovered that sentiment analysis can aid in mood monitoring. People that are depressed exhibit comparable behavior, which may be seen in words shared on social media [27]. As a result, this important information aids in identifying individuals who may be suffering from psychological issues such as depression.

The use of lexical analysis in sentiment analysis is crucial. To diagnose sadness and PTSD, lexical decision lists were employed [28]. Instead of using stemming or spell checking, n-grams and decision lists were employed to evaluate sadness. Using a bag-of-words method, where some terms are more abundant in message categories that we wish to identify, such as depressed or abusive messages, is a typical technique.

The semantic characteristics were analyzed using this method [29]. Using a modified bag of words with Twitter's 140-character restriction to identify the polarity of the data and the preference for 1-gram over n-gram terms, as well as looking at the various syntax employed in Twitter, can help us better extract sentiment from tweets.

3. Methodology

We extracted public data which is available to the public through Twitter's application programming interface (API). This excludes any material that has

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been designated as 'private' by the user, as well as any direct messages.

We retrieved around ten thousand tweets from 100 people in October 2021. The tweets were extracted in three phases. To begin, we created a Twitter crawler using Twitter4j, a Java framework for interacting with the Twitter API. Second, in order to collect sad individuals' tweets, we looked for people who self-declared depression in their tweets and whose bios had explicit and implicit references to depression.

We discovered 30 people on Twitter who were depressed. Then, based on their bio, which includes their true name, work title, and interests, activities, and hobbies, we looked for non-depressed users as a typical group. On Twitter, we discovered 70 people who aren't depressed.

Third, we used our crawler tool to download at least 100 tweets for each depressed user in order to ensure that the contents of the tweets were sufficient to determine whether the user was depressed or not. Then, for each non-depressed person, we crawled the most recent tweets for at least 50 tweets. Only English tweets were retrieved by our crawler technology. Twitter users' timelines were also stripped of URLs and retweets.

Two-phase techniques are used to apply truth labels to the crawled dataset. We screened depressed users in the first phase. In the second step, we proposed that the rest data's manual annotation be based on depression scale tools. To confirm sadness and reduce noise, we utilized the CES-D depression scale.

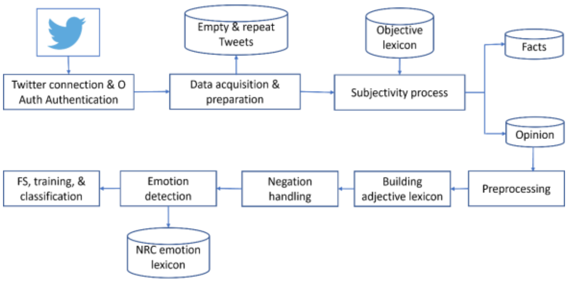

Figure 1. The system architecture of the proposed prediction model

The textual datasets are divided into two types: facts and opinions [30]. Facts are objective knowledge regarding components, things, events, and their qualities, whereas opinions are often subjective representations of an individual's feelings. Many approaches for subjectivity analysis have been developed, including identifying specific patterns of word usage, detecting certain types of adjectives, detecting the existence of emojis, and detecting the occurrences of certain discourse connectives [31].

The tweets are preprocessed to create clean texts for NLP tasks before being used for emotion mining and SA. As shown in Figure 2, the most frequent approaches include eliminating hashtags, URLs, recognizing emoticons, and removing user remarks and unnecessary spaces. To prepare the dataset for stemming, punctuation was replaced with a single space, and spelling correction was performed. Stop words are not useful because we would expect them to be uniformly distributed throughout different texts and easily deleted.

Lemmatization, an enhanced variant of word stemming, removes inflectional ends from words using morphological analysis. Part of Speech (PoS) tagging is also used to label words in a text-based on their nature and connections with other words in the text. Every word has been assigned a tag that identifies its function in the sentence.

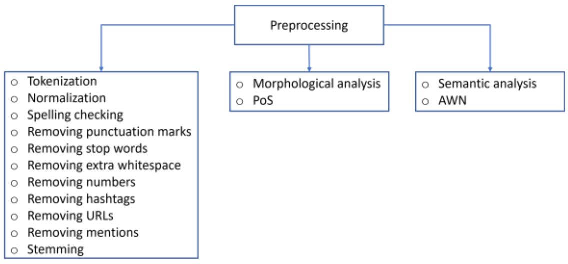

Figure 2. Data preprocessing

Furthermore, we used three machine learning methods (Random Forest, Nave Bayes, and AdaBoostM1) to establish the binary classification of the experimental analysis purpose.

Random Forest is a group of decision trees that have been trained using a bagging strategy, which is one of the ensemble approaches for multiple classifications that divides the dataset into several overlapping subsets. Random Forest is created by training several random decision trees using overlapped subsets of the original data in this manner. The input test sample is categorized using all of the trained trees in the testing phase, and the final output is created based on the output from all of the trees being voted on by a majority of the trees [32].

Bayes' theorem is used to create a probabilistic classifier called Nave Bayes. It is appropriate for high-dimensional data since it assumes that all characteristics are statistically independent of one another [33].

AdaBoostM1 is a weighted sum of multiple classifiers ensemble classification methods. Adaboost's concept is to use another classifier that is stronger in the underlying feature to overcome the limitations of each classifier [34].

4. Discussion and Results

The term "word cloud" refers to a text mining approach that assists in the creation of a story arc. It is made up of a huge number of individual words

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that, when taken alone, may not make much sense; but, when a great number of words are linked together, a distinct image may be drawn. As a result, identifying texts is required in order to extract words from tweets.

Following that, a document term matrix was created using the data that had previously been cleaned and preprocessed. This allowed the most regularly used and referenced words in all tweets on mental health to be highlighted. It's one of the most effective methods for visualizing relevant keywords on a given topic. The most commonly used terms about depression during Covid-19 were examined and represented in word clouds, with the size of each phrase indicating its importance in the text as highlighted in Figure 3.

Figure 3. Instances of word cloud in Twitter data

Figure 4 reports the distribution of the sentiment scores of the tweets in our dataset.

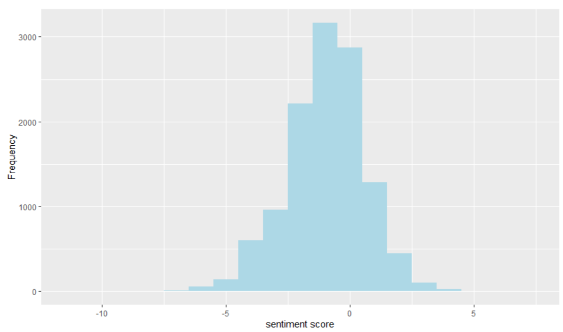

Figure 4. Distribution of sentiment scores of the tweets

We can observe from the histogram of sentiment scores that during COVID-19, the distribution reflects negative sentiment in tweets about depression, which is a key source of worry. The emotion score of more than half of the tweets is negative.

Figure 5 shows a bar plot of the number of tweets vs the polarity classes of tweets on the topic of mental health. Using this bar plot, we can see how people felt about mental health in general during COVID-19.

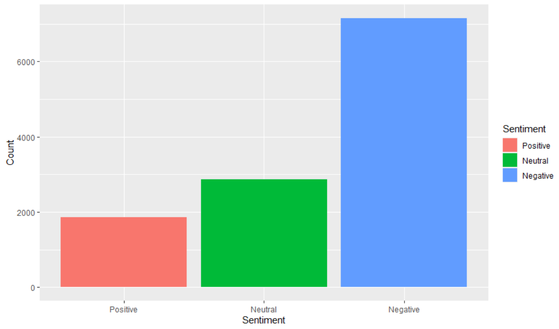

Figure 5. Bar plot of polarity categories vs. the number of tweets

Moreover, half of the tweets have a negative sentiment score, as seen in this bar plot of sentiment type. There are more tweets with neutral emotion than tweets with positive sentiment.

The capacity to count the frequency of words used in a text document or table is one of the most important tasks in Natural Language Processing (NLP). To do this, we must tokenize the words so that they may be counted as distinct objects. The most common word frequency charts in our sample are shown in Figure 6. The most often used phrases in tweets about COVID-19 are "depression," "anxiety," "mentalhealth," "amp," "can," "mental," "health," and so on.

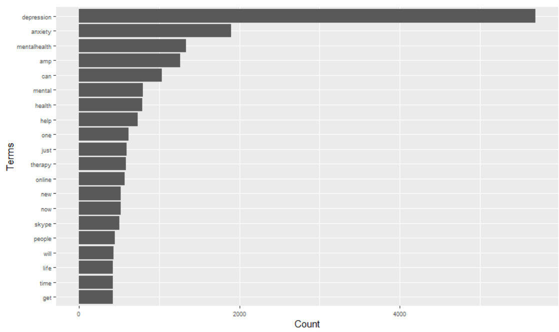

Figure 6. The plot of most common word frequency in tweets

Bigram counts the number of times words appear in pairs in the text. Because bigram is skewed, we use a log transformation to make it easier to see. We utilized the following structure to construct a weighted network from a bigram count: (1) Each word will be a node, (2) two words will be connected if they occur as a bigram, and (3) the weight of an edge will be determined by the number of times the bigram appears in the corpus.

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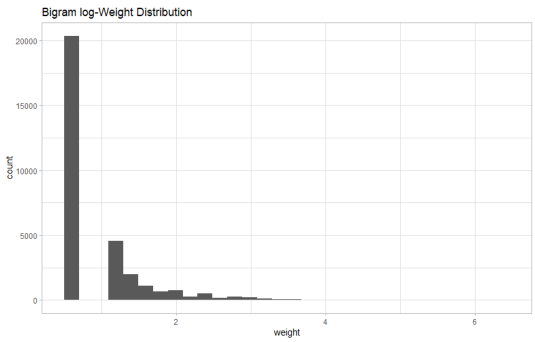

Figure 7. Bigram log-weight distribution of tweets

Figure 7 shows the bigram log-weight distribution. A network diagram is used to show the relationships between terms.

Figure 8. Bigram count network of tweets

Each word has an Arc connecting it to the next. We could visualize all of the links between words at once rather than just a handful at a time.

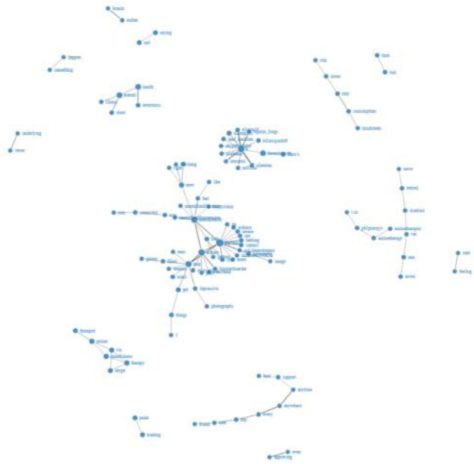

Figure 9. Dynamic Bigram count network of tweets

We can organize the words into a network, as shown in Figure 8, or a more dynamic network, as shown in Figure 9.

Figure 10 presents the accuracy of the three classifiers random forest yields the highest accuracy followed by Naïve Bayes, then AdaBoostM1.

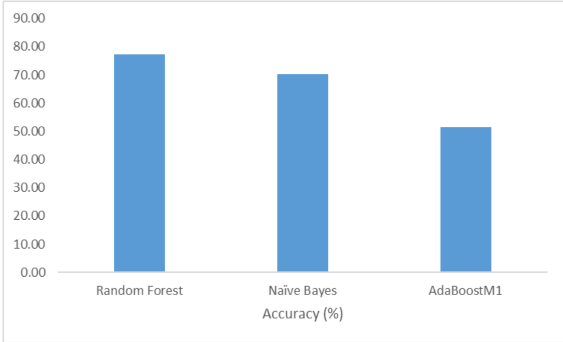

Figure 10. The accuracy rate of three classifiers

5. Conclusion

The sentiment analysis demonstrates how social media may help us better comprehend psychology and human circumstances. Deep learning models' recent developments as a tool for creating strong language models have fueled interest in understanding the temporal dynamics of feelings and mental health during COVID-19. In addition, using a supervised learning method for sentiment analysis, we developed a prediction model to determine whether a user's tweet is depressed or not. We discovered that those who are depressed are more socially isolated, as shown by how they engaged with popular emojis and trending hashtags in their tweets. The Random Forest classifier had the best accuracy.

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