OPTIMIZED NETWORK FOR DETECTING DEPRESSION AMONG TWITTER USERS

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Abstract—The proposed work is to extensively evaluate if a user is depressed or not using his Tweets on Twitter. With the advent of social media, this method should help in identifying the depression of users. We propose an Optimized Network model to evaluate the user tweets on Twitter to analyze if a user is depressed or not. Where the Network is trained using Tweets to predict the polarity of Tweets. The Network is trained in such a way that at any point when presented with a Tweet the model outputs the polarity associated with the Tweet. Also, a user-friendly GUI is presented to the user that loads the trained network in no time and can be used to effectively analyze the users' state of depression. The aim of this research work is to provide an algorithm to evaluate users' sentiment on Twitter in a way better than all other existing techniques.

Index Terms—Depression, Twitter, Sentiment, Social Media

I. INTRODUCTION

Depression is a common mental health condition, it generally constitutes prolonged sadness and lack of interest towards activities that one enjoys doing normally, followed by incompetence to carry out tasks that are carried out routinely for at least a few weeks.

According to studies, there are multiple reasons for depression. People dealing with it often have several problems such as:

• Lack of energy to do routine tasks, physical lethargy
• Inability to sleep properly
• Loss of appetite
• Anxiety
• Shortened concentration towards tasks decisions
• Inability to take
• Feeling of guilt for no reason

In extreme cases, it may lead to self-harm, that in turn may lead to loss of one's life.

One of the common illnesses that is currently prevalent around the world is depression, claiming around 322 million people. Several studies have confirmed that women are more affected than mean due to depression.

Depression is often ignored and not considered as a serious mental health issue due to the stigma attached to mental illness. Unless voluntarily declared by the person suffering due to depression, it is mostly ignored. Around 75% of people suffering due to depression remain unnoticed and untreated in developing countries. Around 1 million people suffer from it each year. It is a serious mental condition and needs to be treated. If not treated it may claim the depressed person's life. 1 in every 13 people suffer from depression globally. An estimated 15 % of people will have an episode of depression in their lifetime.

With the advent of the internet and the widespread usage of Social Network Sites (SNS), people often tend to express their opinion, state of mind, experiences, grieves, happiness on social media. Nowadays people spend more time on their phones, especially social media when compared to anywhere else. This can be used as a fertile ground to understand the state of mind of the user. The presence of a huge amount of data on social media can be exploited by applying various sentiment analysis methods to identify users who are depressed.

Depression on Twitter can be classified into two types:

i) Tweet level

ii) User level

In Tweet level, individual tweets are considered and labeled as depressed or not. In user-level, the history of user tweets is considered to identify if a user is depressed or not.

II. LITERATURE SURVEY

• ***Fine-Grained Sentiment Analysis:*** In this approach other than determining the usual positive, negative and neutral polarity, highly positive and highly negative polarity are also determined. For example: most likely will be classified as highly positive and never will be classified as highly negative.

• ***Emotion Detection:*** In this technique, along with determining the polarity, the emotion behind is also determined like joy, grief, depressed, etc.

• ***Aspect-Based Sentiment Analysis:*** Often it may not be sufficient to know the polarity/sentiment alone. It may be necessary to know what aspect/feature is being discussed. This is mostly useful for companies that are trying to understand what aspect of their product/service their customers are happy/unhappy about.

• ***Intent-Based Sentiment Analysis:*** In this approach, the intent/notion behind a user opinion is analyzed i.e., not just what the user typed but also the intention behind the statement.

Feature engineering is the main concept employed in majority of the studies conducted to identify mental illness expressed on social media. The most popular and widely accepted method for feature engineering is to extract lexical features with the help of Linguistic Inquiry Word Count (LWC) lexicon that consists around 32 categories of psychological constructs [1]. These lexicons have been helpful in key feature extraction mechanism in determining insomnia [2], postpartum depression [3], depression [4] and post-traumatic stress disorder (PTSD) [5]. To identify these mental disorders features had to be extracted such that they overlap with each other while remaining exclusive to a disorder.

The content posted by users on Twitter is unstructured. Due to this nature, it becomes challenging to work with data extracted from these platforms. Character n-gram models are one such model that could be viewed as an inherent technique to reduce the shortcomings posed by unstructured data. Taking into account of such language models in classification tasks using tweets, a unigram and character n-gram language model [6] was used to extract features to detect users at risk of several mental disorder namely PTSD, bipolar disorder, depression and seasonal affective disorder (SAD). According to the procedure mentioned by Coppersmith et al. [6], self-reported data about PTSD was collected from twitter by “The Computational Linguistics and Clinical Psychology (CLPsych) 2015 shared task”. The dataset of the self-reported users were provided to the participants of the shared task. Around 3200 posts were obtained using the Twitter API for each of the users in the dataset.

Likewise, character n-grams are also the key feature extraction mechanism in identifying mental condition such as attention deficit hyperactivity disorder (ADHD), and nine other mental disorder [7], that also includes rare mental health conditions such as schizophrenia [8]. Several studies have identified thatsupervised topic modeling techniques [9] and topics extracted from clustering methods namely Word2Vec and Glove Word Cluster [10] are more dependable in terms of identifying users suffering from various mental condition.

Boot-strapping ensemble framework was proposed by Hassan et al. [15], it is considered a different approach. Data sparsity class imbalance and representational richness issuers could be copied by this framework along with twitter sentiment analysis. Some of the common features namely parts of speech tagging, unigram and bigram we used. In order to determine the overall sentiment, Lexicon-based methods consist of lists of words annotated by their polarity (positive, negative or neutral) or polarity score (positive number or a negative number). The edge of this technique is that it does not require training dataset. However, this technique is not often used in Twitter Sentiment Analysis due to the uniqueness and dynamic nature of data present in twitter with the emergence of hashtags and expression in a timely manner.

SentiStrength developed by Thelwal et al. [16] is a popular lexicon-based algorithm for social media. SentiStrength is highly efficient in identifying the sentiment strength of informal text that includes lexicons that contain words frequently used social media words and phrases. SentiStrength comprises of a lexicon of 700 words, it also recognizes emoticons, supporting words and negations while analyzing the sentiment of a text. Comments from MySpace was used to test the algorithm initially. Later Thelwal et al. [17] extended the algorithm by adding idioms and new sentiment words to the lexicon and applied emphatic lengthening boosting its strength. Many machine-learning techniques were compared against SentiStrength and tested on 6 different datasets that include dataset from twitter.

A three-step technique was proposed by Ortega et al. [18] for analyzing sentiment on Twitter. In the first step, the data as pre-processed and the polarity was detected in the second step. The rule-based classification was performed in the last step. Detection of polarity using rule-based classification was performed based on WordNet and SentiWordNet. When evaluated on the "SemEval 2013" dataset [19] this technique managed to achieve decent accuracy. But, the effectiveness of this algorithm was not determined by comparing it against existing algorithms. Reckman et al. [20] used the same dataset (SemEval 2013) to assess a rule-based system. This system was composed of handwritten rules, where rules had a pattern. That performed significantly well on Twitter sentiment analysis.

Unsupervised sentiment analysis based on emotional signals was proposed by Hu et al. [21]. These emotional signals were branched into two classes namely emotion indicators and emotion correlators.

The concept used to build these signals was orthogonal nonnegative matrix tri-factorization model. This approach was evaluated by using two different datasets and this framework was found to be effective. SentiCircles was one such lexicon-based approach used for twitter sentiment analysis. Firstly, the pre-assigned scores and the polarity of words in sentiment lexicons were updated by taking into account the patterns of words under a different context. This framework was tested using three different datasets. It proved to be extensively effective and outperformed methods based on SentiWordNet.

Ghiassi et al. [22] proposed an interesting hybrid method that combined n-grams and dynamic artificial neural network. Two classifiers namely SVM and Dynamic Architecture for Artificial Neural Networks (DAN2) were built by considering emoticons and tweets that consisted the word hate, love or their synonyms as their feature. This method was evaluated on a corpus of tweets crawled using "Justin Bieber" as the subject. DAN2 outperformed SVM in the test conducted. Kumar and Sebastian [23] presented an approach where they combined log-linear classifier along with dictionary-based method that computed the semantic orientation of adjectives, verbs, and adverbs. The overall sentiment orientation of the tweet was then calculated using a simple linear equation. Also, pre-processing tasks such removal of URL's, hashtags, correction of spellings, removal of replies and parts of speech tagging were performed. Emoticons were substituted by their polarity. This approach could effectively detect the polarity of the tweet as claimed by the authors.

Considering the MapReduce Framework, Khuc et al. [24] created a co-occurrence matrix of bigram phrase. In order to improve the accuracy, this technique combined a lexicon-based approach with a classifier.

III. PROPOSED DATA ACQUISITION TECHNIQUE

Gathering the required data is a challenging task. Here the data is required in 2 forms. Firstly, publicly available labeled Twitter dataset related to depression was collected. In the next phase, Tweets were collected from the respective user Twitter accounts provided they were public. The data collected in the first phase is fed to the model to train the Network. Once trained, the data is collected it is then fed to the model to be analyzed. These results are compared to analyze the accuracy of the model. The contents of the data required are as follows:

- Link to Twitter handle
- To fetch tweets from Twitter a library named “Tweepy” is used. In order to fetch the tweets using Tweepy, 4 keys are required. They are customer_key, customer_secret, access_key and access_secret. For this, we require a developer account and a twitter app should be created. The detailed steps are mentioned in https://developer.twitter.com.

IV. PROPOSED FRAMEWORK

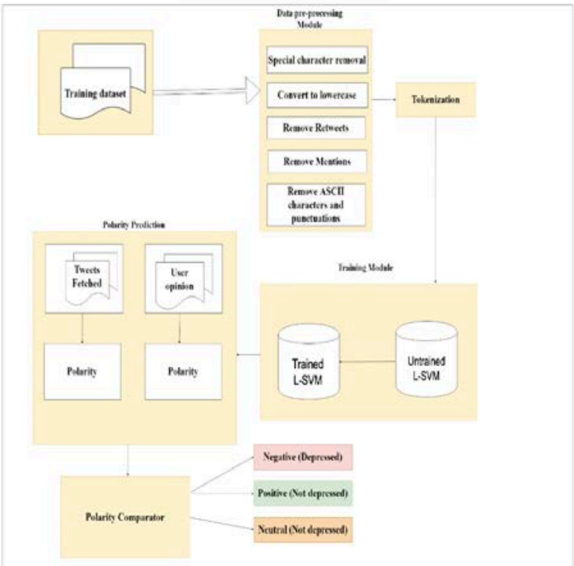


Figure4.1: System architecture of the Depression Detection

The dataset collected during the first phase was publicly available. The data set consisted of 1,00,000 tweetspertaining to different users. The dataset was divided such that 80% of the data was used for training the model and 20% was used for verifying the model. During the training phase the model is fed with the dataset and trained. The datafor the training phase is selected in a random fashion. So that the diversity of the data is even.

Reading training dataset

The dataset collected during the first phase is saved in an excel sheet. This data is first read so that it can be analyzed. The dataset consistsof21 columns, it includes the username, serial number, tweet id, user time zone, sentiment, text, etc. But our model does not require these fields. Only two columns are required for our model, the ”text” and “sentiment “column, and they are read.

Cleaning and Pre-processing

Cleaning and pre-processing is an important step that needs to be performed carefully before carrying out any experiment. Here the text that needs to be cleaned is the one present under “text” column. Normally tweets may contain a lot of noise in the form of punctuation and retweets. Hence, these are removed from the “text” before they can be fed to the training model.

Implement model

Once the network is created then it can be trained using out dataset

Split dataset

Before the model is trained the dataset is divided into two sets, one set for training the model and the other for validating the trained model. The training data constitutes 80% and validation data constitutes 20%. So, the size of training data and test data after division 79991 and 19998 respectively. The division is done randomly with a random state of 42.

Train model

The model is trained using a dataset of 79991 that were cleaned prior to being fed to the model. The model is trained in a sequential recursive manner. Once the system is trained it is ready to be fed with actual user data to predict the polarity of the tweets fetched from Twitter API .

Validate model

The trained model is validated using the data that was split. 20% of the data is used for validating the model. The data obtained from Twitter using the Twitter API is fed to the trained model during the prediction phase. The polarity of the analyzed tweets is produced as output of this phase. For each tweet retrieved the model computes the polarity. The sentiment indicated by the majority of the tweets is considered as the polarity of users. Towards the end of this phase, each user is declared to express either positive, negative or neutral polarity. The model processes and computes the tweets as belonging to one of the polarities.

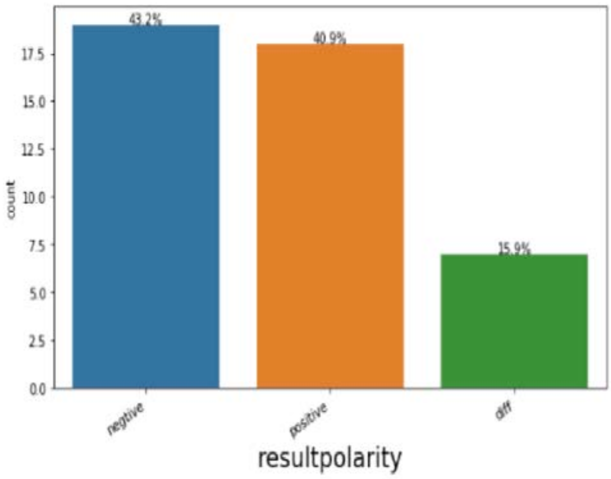
IV .RESULTS AND DISCUSSIONS

From the detailed study conducted and various experiments performed, our model outperforms all the existing techniques. The accuracy attained by our model is 81.82%.

Table 4.1:Summary of Algorithms

Sl. No .	Algorithm	Accuracy %
1	Detecting Depression Using Linear Support Vector machine	81.82
2	Naïve bayes	80.0
3	Decision Tree	63.63
4	Logistic Regression	57.74
5	Radial Support Vector machine	76.36

Figure 4.2:Distribution of result of polarity



V.CONCLUSION AND FUTURE WORK

The usage of social media has grown drastically over the past few years. Social media has become an integral part of our lives. People often tend to use social media to express their emotions. Twitter is one of the primary social media platforms. A comparative study of existing machine learning techniques to identify depression among Twitter users was performed and the drawbacks of all these techniques were reviewed. In our research work we have demonstrated how Twitter can be used as a reliable tool for detecting depression. We constructed an optimized model capable of predicting depression among Twitter users with an accuracy of 81.82% that is, more than the existing techniques available for prediction depression. Also, we have developed a user-friendly GUI for the same. We believe that this model could be a valuable tool in depression analysis. To perform sentiment analysis, the proposed system first fetches the tweets from Twitter using Twitter API and feeds it to the optimized network model to predict depression.

In future work, we plan to develop a social media plugin that tracks the users Tweets and provides them an indication of their depression. Thereby predicting depression at earlier stages. We also plan to extend out work to identify depression among Twitter users based on their gender, geographical location and other demographics.

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