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Mental Health Detection based on Social Media Activities

¹Prof Krishnendu Nair, ² Jadhav Shweta Sanjayrao, ³ Pathare Komal, ⁴Pachpute Sakshi Sunil, ⁵ Rai Anupam

Department of Computer Engineering Pillai College of Engineering, New Panvel, India

Abstract: With the exponential growth in the number of social media users over the past few years, social media has become a primary source of information. Especially among young people, the use of social media platforms, such as WhatsApp, Instagram, and Facebook, to share their thoughts and feelings is becoming increasingly popular. Consequently, there has been a growing research interest in the detection of mental illness by analyzing the user-generated textual content of social media posts.

Social media activities include messages, watchlists, comments on posts, tag lists, and many more. So artificial intelligence (AI) and machine learning (ML)-based models will detect the mental health of the individual. Then it will predict whether the individual is depressed or not. And then accordingly, it will recommend different mental health sites and resources, like psychiatrists, therapists, and hospitals.

For instance, deep learning-based methods such as LSTM are gradually replacing feature engineering-based methods because deep learning frameworks enable models to automatically capture features without the need for time-consuming feature engineering. In addition, pre-trained language models, when trained on mental healthcare datasets, have achieved competitive performance on mental illness detection, which demonstrates their potential value.

IndexTerms – Mental Heatlh, Social Media, LSTM, AI & ML.

I. INTRODUCTION

Mental disorder is defined as a "syndrome characterized by a clinically significant disturbance in an individual's cognition, emotion regulation, or behavior that reflects a dysfunction in the psychological, biological, or developmental processes underlying mental functioning" (American Psychiatric Association, 2013). According to the Canadian Mental Health Association (2016), 20% of Canadians belonging to different demographics have experienced mental illnesses during their lifetime, and around 8% of adults have gone through a major depression. According to World Health Organization (2014) statistics, nearly 20% of children and adolescents have experienced mental illnesses and half of these mental illnesses start before the age of 14.

In addition, around 23% of deaths in the world were caused due to mental and substance use disorders. The broad implication of mental illness can be identified from the level of suicide in Canada where nearly 4,000 Canadians have died from suicide and 90% of them were identified as having some form of a mental disorder (Mental Health Commission of Canada, 2016). Apart from the severity of mental disorders and their influence on one's mental and physical health, the social stigma (e.g., "mental disorders cannot be cured") or discrimination has made the individuals to be neglected by the community as well as to avoid taking the necessary treatments. The inherent complexity of detecting mental disorders using social media platforms can be seen in the literature, where many researchers have tried to identify key indicators utilizing different natural language processing approaches. To extract the most prominent features to develop an accurate predictive model, one must acquire a sufficient amount of knowledge related to the particular area of research. Even if such features were extracted, this does not assure that those features are the key contributors to obtaining improved accuracies. Due to these reasons, we investigate the possibility of using deep neural architectures because the features are learned within the architecture itself. Here, we explore a few selected deep neural network architectures to detect mental disorders, specifically depression. We used the data released for the Computational Linguistics and Clinical Psychology (CLPsych) 2015 shared task (Coppersmith et al., 2015b).

Even though the task is comprised of three subtasks: detecting Post-Traumatic Stress Disorder (PTSD) vs. control, depression vs. control and PTSD vs. depression, our primary objective was to detect depression using the most effective deep neural architecture from two of the most popular deep learning approaches in the field of natural language processing: Convolutional Neural Networks (CNNs) and Long Short Term Memory (LSTM), given the limited amount (i.e., in comparison to most of the

deep neural network architectures) of unstructured data. Our approach and key contributions can be summarized as follows. • Tokenizer: we propose a novel approach to optimize Tokenizer g for classification with a focus on identifying users suffering from depression based on their social posts such as tweets. We use our approach to improve the performance of two tasks: depression detection on the CLPsych2015 dataset and test generalization capability on the Bell Lets Talk dataset (Jamil et al., 2017). • Comparative evaluation: we investigate and report the performance of several deep learning architectures commonly used in NLP tasks, in particular, to detect mental disorders. We also expand our investigation to include different word embeddings and hyperparameter tuning.

A. Fundamentals

As we know, today's generation is fully activated on social media, where they express their feelings, share their thoughts, and explore so many things. On the other hand, let's take a look at the mental health of each one of them. We can say that too many people are facing problems, but they cannot open up with everyone; they express it with only a limited number of people by sharing their thoughts or some posts related to their unhealthy lives, and just like that, there are so many things that we can conclude from taking reference from their social media activity.

Mental health conditions are increasing worldwide. In INDIA about 60-70 million people are suffering from mental health disorders like- personality disorder, bipolar disorder, clinical depression, etc. 1 out of 5 students are suffering from mental health disorders. The majority of people are unaware of their mental health condition and how to deal with it.

The use of social media has increased among all age groups. Sharing feelings, emotions, reviews etc. on social media has become common among youngsters and even other age groups. This system helps people to know if they are suffering from any mental health condition and resources to deal with it based on their social media activities.

B. Objectives

The objectives of a mental health detection project using social media activities can include:

- Early detection of mental health issues: One of the primary objectives of such a project would be to detect mental health issues early on so that individuals can receive the necessary support and treatment as soon as possible.
- **Identification of high-risk populations:** By analyzing the social media activities of different populations, the project can identify high-risk populations that are more vulnerable to mental health issues.
- **Development of targeted interventions:** Once high-risk populations have been identified, targeted interventions can be developed to provide support and treatment to those who need it the most.
- Improved understanding of mental health: By analyzing social media activities related to mental health, the project can help improve our understanding of how mental health issues develop, how they are expressed, and how they can be addressed.
- **Prevention of mental health issues:** By identifying risk factors for mental health issues through social media activities, preventative measures can be implemented to help individuals avoid developing mental health issues altogether.
- **Development of effective mental health policies:** The insights gained from the project can be used to develop effective mental health policies that address the needs of different populations and provide support and resources to those who need it the most.

Overall, the objective of a mental health detection project using social media activities is to improve our understanding of mental health, identify those who are at risk, and develop targeted interventions to provide support and treatment to those who need it the most.

C. Scope

The scope of a mental health detection system using social media is to identify potential mental health issues in individuals by analyzing their social media activity. The system can help detect changes in behavior and provide insights into the severity of the issue. It can also suggest appropriate interventions, such as counseling or therapy. However, it is important to note that this system is not a substitute for professional mental health care and should only be used as an additional tool to aid in mental health detection and support. The scope of the system should be clearly defined and its limitations and potential risks should be identified and addressed.

II. Literature Survey

Depression Detection Using Digital Traces on Social Media: A Knowledge-aware Deep Learning Approach in this research paper's study proposes a deep knowledge-aware depression detection framework using digital trace data on social media, incorporating three categories of medical knowledge to explain the critical factors that contribute to depression detection. It is a deployable tool for many stakeholders, including social media platforms, users, and policymakers.

It works by distributing its work along 3 modules:

Module 1: Here, a function is used:

 $xi \sim = RoBERTa(lei)$

To extract depression diagnosis-related entities from social media posts.

Once this function is solved, it's compared to other users, value to compare the for each entity to determine whether it is experienced by the same user

Module 2: Here, construction of a depression ontology based on medical literature is done. The ontology consists of three subclasses: Symptom, Life event, and Treatment. Semantic textual similarity is calculated using BERT text representation. A Bayesian network is used to approximate the relevance of these terminologies to depression at the population level.

Module 3: In this final module, detection of depression is done. The conventional LSTM model is used which treats each depression diagnosis-related entity equally. Accuracy: 97.56%

1. Depression Detection Using Digital Traces on Social Media: A Knowledge-aware Deep Learning Approach

This study proposes a deep knowledge-aware depression detection framework using digital trace data on social media, incorporating three categories of medical knowledge to explain the critical factors that contribute to depression detection. It is a deployable tool for many stakeholders, including social media platforms, users, and policymakers. [1] Accuracy: 97.56%

2. Identification and Classification of Depressed Mental State for End-User over Social Media

We analyzed and summarized the characteristics of social network behaviors such as network behavior and text semantics (words and topics) of depression groups publishing Weibo. also detected and identified depression through collecting and analyzing college students' microblog social data.) is paper presents a preliminary screening algorithm for college students' suspected depression microblogs, based on depression keywords and semantic expansion. [2]

3. Multimodal Educational Data Fusion for Students' Mental Health Detection

The questionnaire is applied to collect a multi-view social network of students, and this method is time- and cost-consuming and hardly applicable to large-scale. Although we try to automatically capture friendship relationships among students based on cafeteria co-occurrence, such methods are too crude and the accuracy cannot be guaranteed.[3] Accuracy: 80.11%

4. A deep learning model for detecting mental illness from user content on social media

The proposed system shows good accuracy with CNN when compared to XGBoost and detects potential users who may have psychological disorders. More data in the future can help improve the accuracy. [4] Accuracy: 87.4%

5. Social Media Posts as a Window into Mental Health: A Machine Learning Approach

This study demonstrated the potential of using advanced machine learning algorithms to predict mental health status, with Logistic regression outperforming support vector machines and multinomial Naive Bayes.[5] Accuracy: 80%

6. Mental Health Prediction Using Machine Learning: Taxonomy, Applications, and Challenges

Many different techniques and algorithms have been introduced and proposed to test and solve mental health problems. There are still many solutions that can be refined. In addition, there are still many problems to be discovered and tested using a wide variety of settings in machine learning for the mental health domain. [6] Accuracy: 87.50%

7. Detection of Types of Mental Illness through the Social Network Using Ensemble Deep Learning Model

Different types of mental illness are classified using the deep learning model. The ensemble deep learning model is implemented using convolutional neural networks and the recurrent neural network for organizing mental illnesses such as anxiety, bipolar, dementia, and psychosis. The ensemble deep learning model has performed better than the existing models, based on parameters such as accuracy, precision, recall, and F1 score. [7]

Accuracy: 82.4%

8. Text-Based Emotion Recognition Using Deep Learning Approach

This proposed hybrid approach uses the combination of three datasets, namely, ISEAR, WASSA, and the Emotion-Stimulus dataset. The proposed model has many advantages, as it can work on multiple sentences, tweets, dialogs, keywords, and lexicon words of emotions that can be easily detected.

Accuracy: 78.97% [8]

9. Machine Learning-based Approach for Depression Detection in Twitter Using Content and Activity Features

The study classifies and predicts if social media users are suffering from depression or are likely to suffer in the future. It also focused on whether the users' tweets were depressive in nature. This study also aims to detect whether the user is depressed, from the nature of his/her tweets and activity in the network. [9] Accuracy: 82.5%

10. Detection of Depression-Related Posts in Reddit Social Media Forum

Here different Natural Language Processing (NLP) techniques and text classification approaches like bag of words (BOW), Ngrams, LIWC, or LDA are used. The algorithms used are LR, SVM, MLP, and RF. The project also examines the relationship between depression and user's language usage.

Accuracy: 83%[10]

III. Mental Health Detection

A. Overview

As observed in the literature survey; multiple research scholars contributed their work in the domain of detecting depression detection that may occur on social media sites. Hence, the occurrence of this issue was declared mandatory to be detected due to its adverse effects on individuals thus involved. The victim of depression detection felt harassed due to the comments being passed by bullies. The detection of the same is further accompanied by the usage of machine learning and deep learning-based algorithms. Therefore, the author of the proposed research aims to identify the occurrence of such instances that takes place on social media platform such as Twitter. The implementation of the research is further held with algorithms and techniques based on the same. The usage of these algorithms helps to classify the acquired dataset as bullying or non-bullying.

In order to successfully implement the above-mentioned concept; it is important to categorize the obtained comments as bullied or non-bullied. For this to occur; it is a compulsion for ML and DL-based algorithms to understand the sentiment attached to the comment thus being made. The mood of the bully is also taken into consideration to acknowledge the same. The sentiments attached to the comments being made can be categorized into various emotions depending on the intention of the bully. For this to occur, it is required that the words obtained from the dataset must be extracted so that further analysis of sentiments could be performed. Following are the types of features that are expected to be extracted from the words and tweets collected from Twitter-

- Features based on sentiments
- Features based on sarcasm
- Syntactic features
- Semantic features

Based on the above-mentioned features; words from the tweets are respectively extracted. After extraction, they are classified into one of the feature types, resulting in the information from the words being either descriptive or informative. It is worth noting here that; classifying the word features into their respective categories is a significant task. Based on this classification, the final prediction and pattern recognition are performed.

Features that are extracted on the basis of sentiments include words that depict anger, hatred, anxiety, happiness, etc. Such features from the words must be appropriately extracted and classified so that further prediction of bullying comments can be made.

1) Existing System

- With the use of medical domain knowledge, a depression ontology model is built that explains the terminologies used in diagnosis and adds the prevalence of these terminologies to the inference rule.
- Knowledge associated with depression diagnoses in social media posts is derived from the temporal and relevant information, while the temporal information is the recency and frequency of the entities.
- The entities are then used as the input to perform a knowledge-aware deep learning model for binge detection and the attention mechanism is used to perform the entities' temporal and relevance information.
- The results of this research framework can guide interventions for social media users who are at risk of clinical depression and can reduce the societal burden of depression. [1]

2) Proposed System

The previous sections discussed the strengths and weaknesses of the existing system. In order to achieve better domain results, researchers combined both techniques to build Hybrid domain systems, which seek to inherit advantages and eliminate disadvantages.

Data Collection Block: This block is responsible for collecting social media content from various sources, such as Twitter, Facebook, Instagram, etc. Web scraping is a technique that involves automatically extracting data from websites. It can be used to collect real-time data from news sites, blogs, and other online sources.

Preprocessing Block: The collected data is preprocessed to remove noise and irrelevant content, and identify the language of the text. The choice of preprocessing method will depend on the specific dataset and the goals of the analysis. Preprocessing is an iterative process, and multiple methods may need to be applied in order to prepare the data for analysis.

Feature Extraction Block: The AI system performs text analysis on the preprocessed data to extract relevant features such as sentiment, emotion, tone, and topics. For feature extraction, there are multiple steps to be followed like Principal Component Analysis (PCA), Frequency Analysis, Text Mining, Feature Scaling, Feature Selection, and Deep Learning.

Mental Health Indicators Block: The system uses natural language processing techniques to detect potential indicators of mental health issues, such as depression, anxiety, stress, and suicide risk. Also, deep learning is used for post-pattern detection.

Classification Block: The extracted features are used to classify the text into one of several categories such as positive, negative, neutral, healthy, or potentially concerning. In this block we will be using support vector machines for the classification process. Also, decision tree is used for classifying data.

Statistical Analysis Block: The system uses statistical techniques to identify patterns and correlations between mental health indicators and other factors, such as demographics, location, and time of day. Regression analysis is used to model the relationship between one or more independent variables and a dependent variable. This can be done using techniques such as linear regression, logistic regression, or multivariate regression.

Machine Learning Block: The system uses machine learning algorithms to train and improve its ability to accurately detect mental health indicators. Here various algorithms will be used like natural language processing, deep learning, and support vector machines for increasing the accuracy. Also some other algorithms will be used.

Feedback and Reporting Block: The system provides feedback and reports to users, such as mental health professionals, social workers, or the individuals themselves, to help them identify potential mental health concerns and take appropriate action. This will really help a lot to the users so that they will be notified earlier and all the objectives of the project will be fulfilled.

Overall, this proposed system architecture provides a framework for mental health detection using social media activities. By collecting and analyzing social media data, mental health professionals can identify individuals who may be at risk for mental health issues and provide targeted support and resources. However, it's important to note that the system is not a substitute for professional diagnosis and treatment, and users who are identified as at risk should be encouraged to seek help from a mental health professional.

B. Implementation Details

Cleaning & Preprocessing :

We first convert the tweets CSV file into a Pandas dataframe. Following are the steps we will perform for the preprocessing the data using the NLTK:

- o Remove HTML entities
- o Substitute @mentions, urls, etc. with whitespace using regular expressions
- o Substitute any non-alphabetic whitespace.
- o All the words in lowercase.
- o Removing stop words.
- o Punctuations

Exploratory Data Analysis (EDA):

- o Count plot of target class
- o Word Cloud

countplot():- method is used to show the counts of observations in each categorical bin using bars Word Cloud :- data visualization technique used for representing text data in which the size of each word indicates its frequency or importance.

Machine Learning Algorithms

The use of machine learning is widely adopted by multiple scholars for the prediction of sentiment analysis. The primary reason for this is the time complexity of the machine learning algorithm which is speedier than that of lexicon-based technique. The sequential flow of machine learning involves the implementation of respective algorithms that are used to train and test the system model and further use them for the final prediction of depression detection cases. For the purpose of implementation of the proposed thesis, the author has used machine learning algorithms and deep learning-based algorithms.

Deep Learning Algorithms

The volume of data that machine learning algorithms handle is one of their main difficulties. This user-generated data was found to be complicated in character, which enhances the overall operation of real-time depression detection. Additionally, the bully's anonymity stays hidden, making it impossible to identify the source of the posted texts and comments. Additionally, there are some well-known differences in users' mental, illness, and religion that further fuel animosity and encourage the emergence of depression. Numerous study academics have been able to identify depression detection using various technologies as a result of the growing observation of depression occurring online. To categorize such remarks as positive or negative in this situation, the ideas of automated and computational methods have been crucial. Researchers have been adding their work in the same field and have become quite interested in this automated depression detection method. The identification of real-time depression detection situations is one of the most significant issues a deep learning system has when trying to detect the same. A machine learning

system cannot produce better results due to the vast amount of data created because the content needs to be semantically examined. In a machine learning algorithm, the methods utilized to extract the appropriate features also grow. Despite the fact that lexical methods can also be used, they do not offer the best detection of depression detection. They are implemented as neural networks that contain neurons. These algorithms operate by executing the hidden layers that are involved in them and are capable of handling massive amounts of data efficiently.

CNN with TF-IDF Vectorizer

The working implementation of a CNN can be described through the layers as explained below

Convolutional layer: the convolutional layer is the primary layer through which the implementation begins. The layer is 0 therefore responsible for collecting and gather inputs from the variables thus given. The input is further converted to its respective convolutional size and forwarded to the next layer as an output. The convolution in this layer takes place through matrix operation and the resulting output is thus served as an input to the next layer

Activation layer: the layer next to the convolutional layer is the activation layer wherein the triggering of weighted neuron 0 occurs. The triggering point takes place on the basis of weights assigned to each and every neuron. The assigned neuron is triggered when the predicted output matches to that of the actual output. This enables the process of forward propagation. On the other hand, if the predicted output does not match with the actual output; the neuron is triggered in the backward direction. This is referred to as backward propagation. However, the entire process of neuron trigger is enabled once the associated weights and biases are assigned to them. The performance factor of this layer is evaluated through the activation function. Multiple activation functions can be used to execute the same such as ReLu, tanh, and Sigmoid

o Pooling layer: this layer is responsible for putting together and combining the outputs of both the layers as mentioned above. The output of this layer is further fed as the input to the next layer

o Fully connected layer: this is the last layer of the CNN and tends to generate the final output for the same. Hence, the fully connected layer also comprises of various hidden neurons in it to carry out the required convolution



After the execution of all the layers in the CNN model; further vectorization of semantic words takes place through the TF-IDF vectorizer.

LSTM with tokenizer

A variation of the RNN model is the working implementation of the LSTM model. A primary function of the LSTM model is to handle issues with respect to long term dependencies. The conventional structure of an RNN follows the components of repeated modules. The repeated modules are in the form of chain modules which are iterative in nature. The iterative module also consists of a tanh layer. The repeating structure of the RNN model is depicted in figure below:



Following are the components of the LSTM model:

- Forget Gate (f)
- Candidate layer (g)

- Input gate (I)
- Output gate (O)
- Hidden state (H)
- Memory state (C)

The architecture of the LSTM model is depicted in diagram below:



The input, output and forget gates of an LSTM are implemented through the activation functions of sigmoid. Hence, the output thus generated through Sigmoid is presented in the range between 0 to 1. The output of 0 indicates the neuron is backwardly propagated whereas the output of 1 indicates forward propagation of the same. On the other hand, the function of the forget gate is to manage the number of states for each and every propagation thus made due to trigger of neurons. The forget gate controls the number of neuron states which are previously passed. The hidden state of LSTM maintains the number of hidden layers in each LSTM model and manages the dimensions of the same. Finally, the memory state is responsible to measure, monitor and control all the states of the model and further generate the output on the basis of neuron values generated using the sigmoid function.

When this implementation of an LSTM model meets the requirements of a tokenizer; the working execution is labeled as LSTM with tokenizer which is henceforth used for the purpose of implementation of the proposed thesis. A tokenizer works by separating all the involved words in the phrases by forming individual tokens. The num_words is used as the syntactic parameter to implement the same. This parameter is assigned to count the number of words and calculate the maximum length of the phrase. In the next stage; words are broken into tokens and each token is assigned a number. This number is further used to refer to the respective word from the phrase. The implementation of an LSTM based tokenizer is done on Keras and thus a string of words are broken.

IV. Result and Discussions

A. Standard Datasets Used

The dataset contains about 11 columns with information about the user who posted the tweet, post id, date the post was created and the target label. There are 20000 rows and tweets in the dataset, out of which no fields are missing or duplicated.

The data is in an uncleaned format and is collected using Twitter API. The Tweets have been filtered to keep only the English context. It targets the mental health classification of the user at Tweet-level. Also, check out notebooks.

B. Evaluation Parameters

Predictive accuracy metrics treat all items equally. However, for most recommender systems we are primarily concerned with accurately predicting the items a user will like. As such, researchers often view recommending as predicting good, i.e. items with high ratings versus bad or poorly-rated items. In the context of Information Retrieval (IR), identifying the good from the background of bad items can be viewed as discriminating between "relevant" and "irrelevant" items; and as such, standard IR measures, like Precision, Recall and Area under the ROC Curve (AUC) can be utilized.

Precision: measure of exactness, determines the fraction of relevant items retrieved out of all items retrieved

 $Precision = \frac{tp}{tp + fp} = \frac{|good movies recommended|}{|all recommendations|}$

Recall: A measure of completeness, determines the fraction of relevant items retrieved out of all relevant items.

Depression Type	precision	recall	f1-score	support
0	0.87	0.80	0.83	1981
1	0.82	0.88	0.85	2019

Table 1. Evaluation Metric

Hybrid models discussed in the work, two techniques have merged in four different ways. The first one works by combining the separate recommender ratings using a linear combination or a voting scheme which basically selects the recommendation that is seen better in terms of quality and more consistent with past users' ratings. As for the second method, it adds the content-based characteristics to collaborative models which can help in overcoming the sparsity problem since we are not only relying on ratings but also on item profiles for our prediction. The third way is to add collaborative characteristics to content-based models where latent factors are introduced to describe the user preferences. The fourth mode is to develop a single unifying recommendation model based on content-based and collaborative characteristics using probabilistic approaches such as rulebased classifiers or Bayesian regression models.

To select the optimum values, the weights α and β have to be selected to maximize the accuracy of the resulting MAE evaluated with the combined rating. Alternatively, the choice of the weights needs to minimize the error resulting from the difference between predicted ratings and actual ratings available in training data. For each rating-prediction pair <pu,ru>, pu being the predicted value and qu the correct value available in the training data, the absolute error is computed as |pu-ru|. The MAE is then evaluated by examining N ratings-prediction pairs, and computing the average error as shown in equation(9) above. The lower the MAE the better the accuracy is. As a result, the choice of the weights (α, β) needs to minimize the MAE.



Result of the model

V. Conclusion

We have successfully implemented CNN model and used lstm algorithm to predict if an individual is depressed or not. By increasing the dataset, it can be helpful for self-diagnosis of depression of an individual.

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