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SEARCH MENTAL PROBLEMS USING SOCIAL MEDIA IN EMOTIONAL PATTERNS

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ABSTRACT: Today the World Health Organization (WHO) people are affected by mental disorders some point in their lives. A timely finding some problems is challenging but important, it could open the possibility to offer a bid to people before the illness gets worst. To take number of social media users and the tremendous quantity of user-generated data on social platforms give unique opportunity for researchers to distinguish patternsis correlated with mental status. We developed deep learning models to learn linguistic markers of disorders at different levels of the language and further try to interpret the behaviour of our models for a deeper understanding of mental disorder signs. Our proposed system is different from other work in this area in that our system is based entirely on the emotional states and the transition among these states of users on Reddit in prior work is typically based on contentbased representations. We present our research is better visualising and understanding the factors that characterise and differentiate social media users is affected mental disorders from those who are not. We believe our model can help identify potential sufferers with mental illness based on their posts. This study further discusses the implication of our proposed model is supplementary tool for monitoring mental health states of individuals find frequently use social media. Finally leveraging the data of social connections between eating disordered different Twitter today the first homophily study number of eating-disorder communities in social media. Our findings shared new light on eating-disorder community develops on social media.

INDEX TEARMS: Emotional Disorders, Unprompted Detection, Emotional States, Emotion Classification, Reddit, Social Media, Cognitive styles Deep learning

1. INTRODUCTION

Mental disorders affect a large segment of the public is report from 2018 estimated that 28.9% of all U.S. adults have some type of

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mental health issue [1]. The COVID-19 pandemic has most likely raisednumber to the National Institute of Mental Health (NIMH) the prevalence of anxiety major depressive post-traumatic stress and bipolar disorders number of U.S. adults aged 19 or older is much higher than the prevalence of other mental disorders [2]. Common mental disorders such as depression is affect several millions of people total world. They may be connected to a single incident which can cause more stress on the person or by a combination many stressful events [3]. It is also known that mental disorders tend to grow in countries containing generalized violence in recurrent natural disasters [4].Social media platforms are increasingly widespread many people nowadays to express their feelings and moods [5]. As a result of this phenomenon researchers and healthcare professionals is classify linguistic indicators related to mental illnesses like schizophrenia depression and suicide [6].The way mental disorders manifest is recognized is primarily through everyday communication. It has been take previous computational studies that individuals suffering from mental disorders manifest changes in their language and their behaviour [7]. Emotions ismanifested in many different modalities such as text image, audio, and video which makes emotions by nature a multimedia phenomenon [8]. In this paper although we only focus on the emotions represented by text which is one of the most common representations of emotions on social media the methods proposed here is easily extend to other modalities [9]. We take many methods for visualising the data in order to provide useful insights to psychologists we first compare users affected by a particular disorder against control individuals [10].

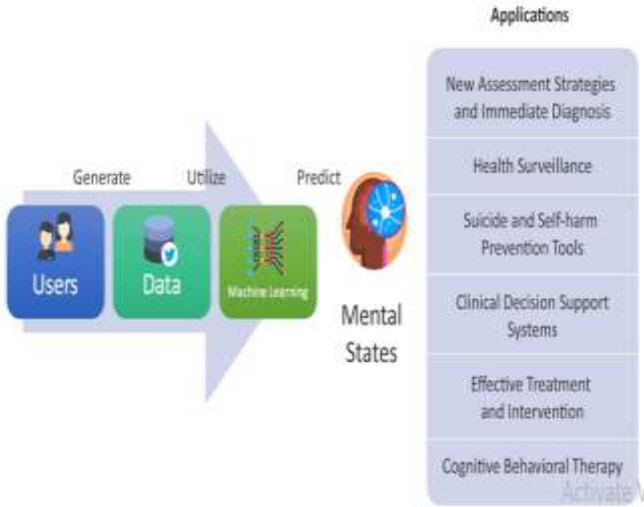

Figure1: Research on e-mental health through social media: a conceptual framework

2. RELATED WORK

The largamente of the works in the area is mostly focused on the automatic identification of mental disorders in social media we outline some effort is devoted to better understanding the relationship many language and mental disorders in social media is relevant to our work [11].We next collected post data from the most popular health-related subbed it mental health, to find the posts with general health information [12]. From everysubedit we collected all the user IDs who had at least one post related to the mental health [13]. A recent work measures the psychological features in a “pro-anorexia” community on Twitter [14]. The community studied in this work is a group of users who talk about ED in their tweets and

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this typically includes not only people who are really affected by the condition but also a large number of people who casually discuss the disease on a one-off basis [15]. In factpsychologists are demonstrated that the patterns with different emotional disorders are different from those of emotionally healthy many regarding emotional reactivity and regulation [16].They characterize users affected by mental disorders and propose methods for visualizing the data in order to give useful insights to psychologists. Lastly, some works is considered representations based in sentiment analysis model [17].

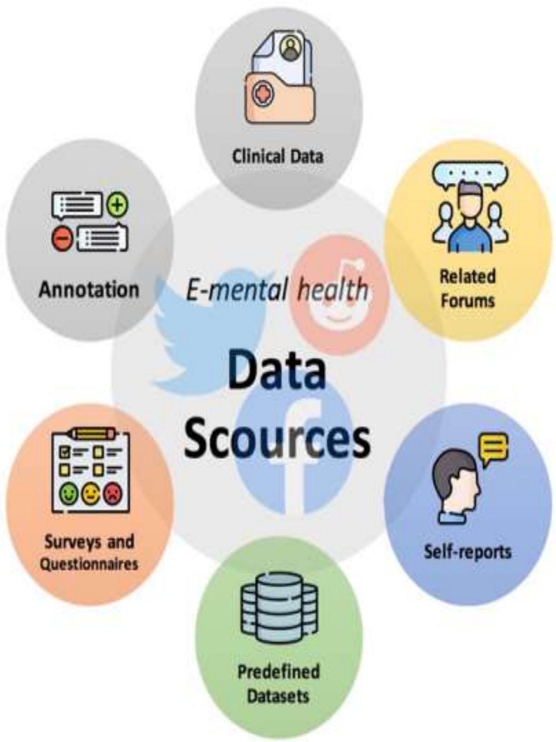

Figure2: The data source for e-mental health research

3. SYSTEM MODEL

Building predictive models using extracted data is the process of automating the analysis of social networks [18]. The social data collected in social media networks come from user's online mode. The content is include text, images, videos, context data user biographical information, connections, and interests [19]. We maintain the original data split provided by the shared task organizers to ensure consistency and comparability with backend results even though the test sets are sometimes larger than the training data sets [20].We also experimented with leveraging multi-label classifiers to label many emotions but the results were much poorer than having some binary classifiers.Individuals usually convey emotions feelings and attitudes in the words they use. For instance gloomy and cry denote sadness whereas delightful and yummy evoke the emotion of joy [20].

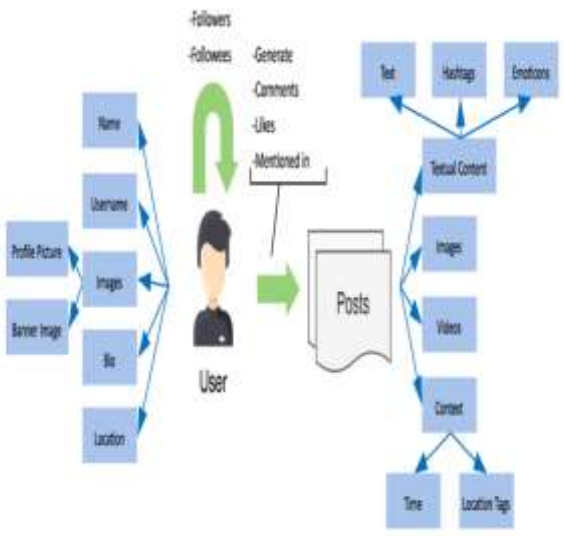

Figure3: Principal components and relationships in social data

4. PROPOSED SYSTEM

To offer a glimpse of the data sets we demonstrate some examples of posts from the different classes of users [21]. Our goal to

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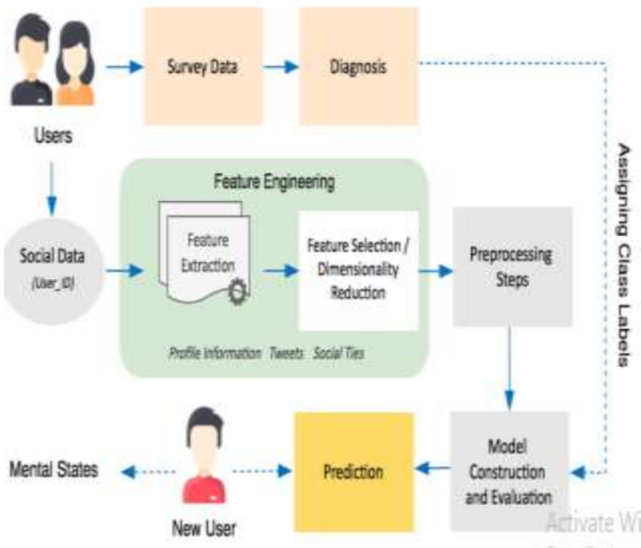
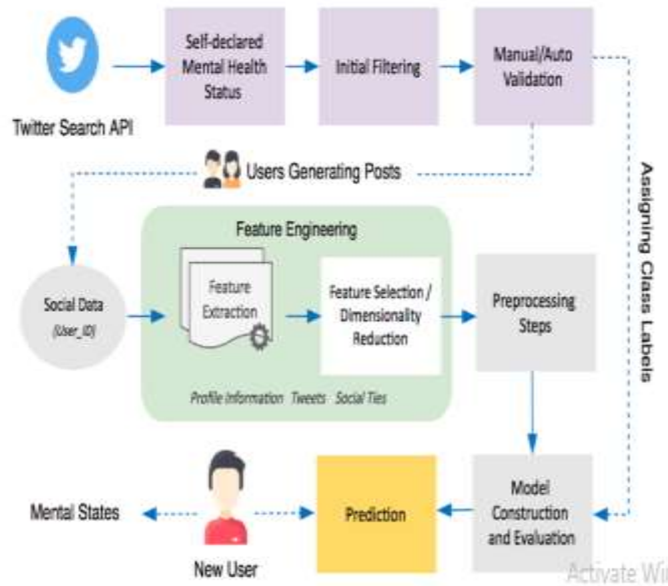
users who effect from a mental illness as well as controlusers share their experiences and personal feelings about them which for both be positive and negative making their detection a great challenge [22].Additionally to avoid inadvertently training a topic classification model instead of an emotional disorder detection model, we controlled the topic similarity of different groups. To security of the topics discussed by the users in the control group are similar to those talked about by users with emotional disorders [23]. Our surpassing state-of-the-art results in mental disorder finding but rather providing a deeper understanding of the way they manifest in language backed by theories in psychology.



A) Survey-based analysis



B) Self-report-based analysis

Figure5: The mental health prediction via social data

1. PREDICTION ALGORITHM

Machine learning algorithms learn patterns from data in selected features as training sets [24]. Five broad categories of machine learning algorithms is presented here supervised, semi-supervised, unsupervised, reinforcement and deep learning

Step1: Supervised learningsupervised learning take presenting algorithms for training instances consist of inputs and outputs. Inputs are often represented as numerical arrays and itdescribe numerically.

Step2: Unsupervised learning take supervised learning it is uses to find the classes in naturally arise from a similarity in input data instead of knowing the output variable is training time Identifying groups of users with same characteristics

Step3:Semi-supervised learning Semi-supervised learning take a large number of

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training samples is available but the output labelsis only known for a small percentage of samples trained to take labelled and unlabelled instances in semi-supervised algorithms

Step4:Reinforcement learning Reinforcement learning is uses to agents learn through trial-and-error interactions with their environment. Depending on the current state an agent will decide the action to take in order to maximize its rewards.

Step5:Deep learningin research oriented on e-mental health has been boosted recently deep learning is rapidly-expanding field of machine learning. In contrast to statistical methods deep learning uses neural networks usually number of data hidden layers to learn many abstraction levels

A. Transfer learning transfer learning to process developed for a task to develop a model for another one an initial point for NLP and computer vision using pre-trained algorithms is a popular approach in deep learning [25].

2. **CLASSIFICATION MODELS**.

We developed binary classification models everycategorizes a userspecific post into one of the conjecture is that a user who suffers from a specific mental problem writes a post on the corresponding subedit that deals with the problem. A user can write posts across multiple subedits if he/shesuffers from multiple mental health problems [26]. The proposed CNN-based architecture is used to sequence of layers that includes embedding layer convolutional layer max-pooling layer dense layers, and the output in the given model. Tofirst layer of the model is an embedding layer that represents the word embedding's of a pre-processed post with 30 dimensions and its weight is initialized by the pre-trained word3vec.

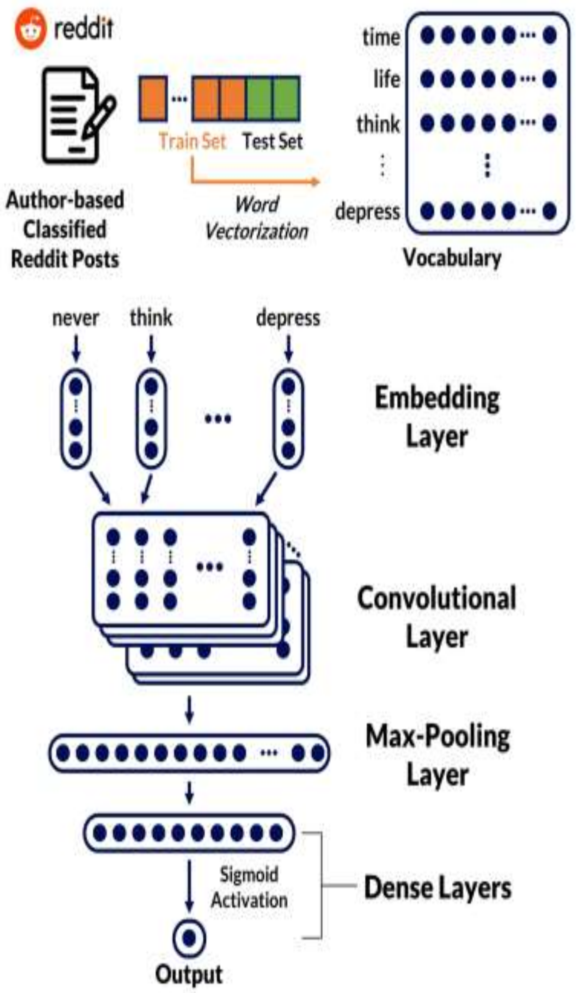


Figure6: Architecture of the proposed CNN-based classification model.

5. COMMUNITY CHARACTERIZATION

Different connect/interact with others and form communities on Twitter primarily by four ways: “follow”, “retweet”, “reply” and “mention”. According to follow, re-tweet, reply and mention ties many users we build many types of weighted and directed networks many usersfollow, re-tweet, reply and mention networks, respectively the re-tweet, reply and mention ties are extracted from users' most recent posts retrieved [27]. We investigate the characteristics communities based on these networks.

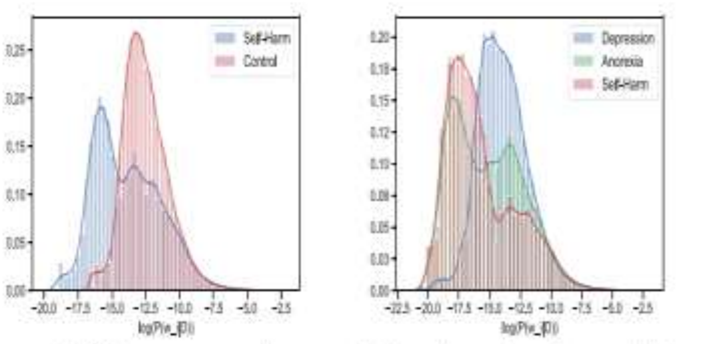
Network Characterization We first examine the network features of different types of network models to built. We measure networks by using nine types used metrics:

1. Total number of nodes
2. Total number of edges
3. Edge density
4. Average shortest path length of connected node pairs
5. Total number of weakly connected components
6. Fraction of nodes in the giant weak component;
7. Global clustering coefficient
8. Reciprocity
9. Assortativity coefficient of degree

Homophily Analysis Homophily is the tendency of individuals to connect with others who share similar characteristics the properties of homophilyis understand the way a community develops

6. RESULT AND DISCUSSION

Bag of Emotions (BoE) acts like a description which are used to measure the emotional valence or polarity in the posts A Bag of words (BoW) is a representation of text that describes the occurrence of words within a document.The datasets we use contain long histories of social media activity for each user possibly including texts written before the users were diagnosed with the mental disorder which makes it suitable for evaluating early detection and for analyses of the evolution of symptoms over time. The most remarkable case is the difference found in the use of the pronoun "I" between positive and control users, which in the case of depression replicates previous findings for other social media platforms.



(a) Self-harm vs. control (b) Anorexia vs. depression vs. self-harm

Figure7: Language models probability distribution comparison

7. CONCLUSION & FUTURE WORK

To the best of our knowledge is the first to leverage emotion states for identifying users with in emotional disorders on social media. For task we propose a topic-agnostic method is based on an emotional transition probability matrix generated by the emotion states in user-generated text. We showed that deep learning models is useful for successfully detecting social media users to risk developing a mental disorder in the texts they post online are represented with linguistic features at different levels. We presented a series that examines the language and behaviour of people enduring mental disorders and discussed diverse aspects associated with developing experimental frameworks. We also plan to study whether other non-content features is helpful for identifying users with emotional disorders. Finally a future research is to integrate other modality such as image, audio, and video into our model to strengthen its performance generalizability and interpretability.

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