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# DETECTING MENTAL DISORDERS IN SOCIAL MEDIA THROUGH EMOTIONAL PATTERNS THE CASE OF ANOREXIA

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## ABSTRACT

According to the World Health Organization (WHO), one in four people will be affected by mental disorders at some point in their lives. However, in many parts of the world, patients do not actively seek professional diagnosis because of stigma attached to mental illness, ignorance of mental health and its associated symptoms. In this paper, we propose a model for passively detecting mental disorders using conversations on Reddit. Specifically, we focus on a subset of mental disorders that are characterized by distinct emotional patterns (henceforth called emotional disorders): major depressive, anxiety, and bipolar disorders. Through passive (i.e., unprompted) detection, we can encourage patients to seek diagnosis and treatment for mental disorders. Our proposed model is different from other work in this area in that our model is based entirely on the emotional states, and the transition between these states of users on Reddit, whereas prior work is typically based on contentbased representations (e.g., n-grams, language model embeddings, etc). We show that content-based representation is affected by domain and topic bias and thus does not generalize, while our model, on the other hand, suppresses topic-specific information and thus generalizes well across different topics and times. We conduct experiments on our model's ability to detect different emotional disorders and on the generalizability of our model. Our experiments show that while our model performs comparably to content-based

models, such as BERT, it generalizes much better across time and topic.



**INTRODUCTION;**

Mental disorders affect a large segment of the public. A report from 2017 estimated that 18.9% of all U.S. adults have some type of mental health issue [21]. The COVID-19 pandemic has most likely increased this number [6]. According to the National Institute of Mental Health (NIMH), the prevalence of anxiety, major depressive, post-traumatic stress, and bipolar disorders among U.S. adults aged 18 or older is much higher than the prevalence of other mental disorders. As stated by the Diagnostic and statistical manual of mental disorders (DSM-5), mood features are the most important and essential features for diagnosing anxiety disorders (AD), major depressive disorder (MDD), and bipolar disorder (BD). According to DSM-5, anxiety disorders are a set of disorders which share features of excessive fear and anxiety; features of major depressive disorder include loss of interest or pleasure in most activities and having consistent depressed moods; bipolar disorder (BD) is a mood disorder characterized by the existence of at least one manic or hypomanic episode and one depressive episode [2]. Though prevalent in U.S. adults, post-traumatic stress disorder is not as closely related with mood as the other three disorders; it mainly is based on the experience of a shocking, scary, or dangerous event. In this paper, we focus on the three common mental disorders (AD, MDD and BD) which are closely related with mood. Considering their close relationship with emotions, we refer to them as emotional disorders. 1 These disorders can cause great impairment in daily functioning and are often assessed through clinical interviews, brief self-rated and clinician-rated measures. Bipolar and related disorders are often related with great impairment in marital and work functioning and increased risk of suicide [20] and Mood Disorder Questionnaire (MDQ) is used for identifying clients. major depressive disorder is associated with impaired cognitive and social functioning [18, 26] and Patient Health Questionnaire (PHQ-9) is used for recognizing clients. People diagnosed with anxiety disorders overestimate danger in certain situations and exhibit avoidance behaviors that prevent them from functioning normally and we use Generalized Anxiety Disorder Screener (GAD-7) to figure out clients. Although these inventories have outstanding screening sensitivity and specificity, they have one significant problem. Because patients must take the initiative and be proactive in participating in completing these inventories, often times potential patients are unwilling to take the survey which will cause undiagnosis or misdiagnosis. Nearly two-thirds of people with a known mental disorder never seek help from a health professional because of stigma, discrimination and neglect [24]. This problem is complexified by the fact that some emotional disorders will also prevent patients from seeking help. For example, clients with major depressive disorder might not have the energy to proactively seek help, and bipolar disorder is often misdiagnosed for major depressive disorder wrongly because people experience more subjective stress to seek help during the depressive episode [16]. To address this problem, unprompted screening tools have been receiving more attention in recent years, especially those leveraging social media data to gain insight into people’s mental states. Most of the existing unprompted screening tools are based on psycholinguistic analysis of the content of user-generated text. For instance, the use of absolutist words [1] or the use of first-person pronouns [27, 33, 34], have been shown to be predictive of emotional disorders. However, these content-based features capture "vulnerability factors" which still exist even after patients have recovered [1] and are influenced by topical information [17], which raises doubts about the generalizability of the current unprompted screening models and, at best, limit their applications. To overcome the shortcomings of unprompted screening models based on content representations, we propose an unprompted screening model based on the transition between different emotions expressed by the users on social media. This is inspired by the fact that emotions are topic-agnostic and that different emotional disorders have their own unique patterns of emotional transitions (e.g., rapid mood swings for bipolar disorder, persistent sad mood for major depressive disorder, and excessive fear and anxiety for anxiety disorders). Specifically, we create an emotional "fingerprint" for each user by capturing their transition probability matrix of different emotional states. We hypothesize that there will be similarities in the emotional fingerprints between users with similar mental disorders, which can be used for unprompted detection of such disorders. Moreover, our emotion-based model provides greater interpretability, making it more acceptable to mental health clinicians. Emotions can be manifested in many different modalities such as text, image, audio, and video which makes emotions by nature a multimedia phenomena. 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 can be easily extend to other modalities

**RELATED WORK** In recent years, social media has become a valuable source for emotional disorders identification and analysis. Several studies have used Twitter data to detect users with major depressive disorder [11], post-traumatic stress disorder (PTSD) [10] and bipolar disorder [5, 8, 9]. Reddit has also been used for studying emotional disorders; specifically for psycholinguistic analysis of emotional disorders [7, 12, 17, 27, 36], the detection of posts indicating anxiety disorders [31] and the detection of users with emotional disorders [29, 32] . Previous approaches to detect users with emotional disorders have usually relied on the linguistic and stylistic features of usergenerated text [8, 29, 29, 31, 36]. Inspired by the great success of deep learning methods in the field of natural language processing, deep learning models have also been used for this task. Feature attention networks [32] and hierarchical attention networks [30] which extracts features at post-level and concatenates them at user-level have been built for detecting users with major depressive disorder. These models have shown high interpretability but limited improvement in performance. While concatenating all posts of a user has been shown to be better for this task due to its capture of global features, the interpretability of the model is limited because of its multi-channel design [23]. However, no existing approaches have focused on the patterns of emotional transition of users, which is not only the core characteristic of emotional disorders, but is also more robust to domain and topic information. In fact, psychologists have demonstrated that the patterns of individuals with emotional disorders are different from those of emotionally healthy individuals regarding emotional reactivity and regulation. For instance, in social anxiety disorder, negative emotions can be detected constantly because of problematic emotional reactivity and deregulation [19]. At the same time, individuals with major depressive disorder are more likely to be unable to shift from negative emotions to positive emotions compared with healthy individuals [25]. Built on previous research, we proposal the ER method to represent user posts which is based on the patterns of emotional transition of users, and focus on the global features

**EXISTING SYSTEM**

Depression is a mental health disorder characterized by persistent loss of interest in activities, which can cause significant difficulties in everyday life [1], [17]. Studies focusing on the automatic detection of this disorder have used crowdsourcing as their main strategy to collect data from users who expressly have reported being diagnosed with clinical depression [18], [19]. Among these studies, the most popular approach considers words and word n-grams as features and employs traditional classification algorithms [13], [20], [21]. The main idea is to capture the most frequent words used by individuals suffering from depression and compare them against the most frequent words used by healthy users. This approach suffers because there is usually a high overlap in the vocabulary of users with and without depression.

Another group of works used a LIWC-based representation [22], aiming to represent users' posts by a set of psychologically meaningful categories like social relationships, thinking styles, or individual differences [18], [23]. These works have allowed a better characterization of the mental disorder conditions, nevertheless, they have only obtained moderately better results than using only the words. Recent works have considered ensemble approaches, which combine word and LIWC based representations with deep neural models such as LSTM and CNN networks [24], [25]. For example, in [25], [26], the combination of these models with features like the frequencies of words, user-level linguistic metadata, and neural word embeddings offered the best-reported result in the eRisk- 2018 shared task on depression detection [27].

These works show that in social media texts exist useful information to determine if a person suffers from depression, but the results are sometimes hard to interpret. This is an important limitation since these types of tools are naturally aimed to support health professionals and not to take the final decisions. In [28] [29], the authors conduct studies to tackle this problem. They characterize users affected by mental disorders and provide methods for visualizing the data in order to provide useful insights to psychologists.

**DISADVANTAGES**

1) The system doesn't implement Converting text to sub-emotions sequences techniques.

2) The system doesn't implement emotion based detection of mental disorders.

**PROPOSED SYSTEM**

The proposed static and dynamic representations, named as BoSE and _-BoSE respectively, are inspired in two hypotheses. The first one is that words assigned to coarse emotions in lexicons cannot capture subtle emotional differences, which in fact are what provide the most important insights into the mental health condition of users. For example, the lexicon associated with the anger emotion includes words such as furious, angry and upset that represent different degrees of anger, however, they are tagged with the same emotion. Thus, our proposal is to represent each user by a histogram of sub emotions, which are discovered by clustering the embeddings of words inside coarse emotions. The second hypothesis is that people with depression and anorexia tend to expose greater emotional variability than a healthy person. In this case, the idea is to represent each user by a set of statistical values that describe the frequency changes of the sub-emotions over time.

**ADVANTAGES**

1) The system further explores the BoSE representation and proposes a new representation based on sub-emotions that allow capturing the emotional variability of social media users over time.

2) The system proposes an approach to combine both static and dynamic representations using early and late fusion strategies to improve the detection of depression.

3) The system extends the use of these representations based on fine grained emotions for the task of anorexia detection and contrast the discovered emotional patterns with those obtained from the task of depression detection.

**Modules**

**Service Provider**

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Login, Browse and Train & cd Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Tweet Message Type, View Tweet Message Type Ratio, Download Trained Data Sets, View Tweet Type Ratio Results, View All Remote Users.

**View and Authorize Users**

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

**Remote User**

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT TWEET MESSAGE TYPE, VIEW YOUR PROFILE.

**CONCLUSION & FUTURE WORK** To the best of our knowledge, this paper is the first to leverage emotion states for identifying users with emotional disorders (bipolar, depressive, and anxiety disorders) on social media. For this task, we propose a topic-agnostic method based on an emotional transition probability matrix generated by the emotion states in user-generated text. We find that a simple random forest classifier trained on a 17x17 emotional transition matrix can outperform a more complex tf-idf based classifier and perform comparably to a BERT classifier. More importantly, our approach, different from content-based representations influenced by topic, domain, and information leakage, is more robust and has better interpretability. In our future endeavors, we plan to further validate our emotion representations by exploring a wider range of classifiers. Moreover, to test whether our method is platform independent, we plan to extend our approach to other social media platforms, such as Twitter. Additionally, our current approach of using an emotion classifier to characterize the emotional states of users can be improved by either having more accurate emotion classifiers or by exploring new methods to characterize the emotional states of users. We also plan to study whether other non-content features (e.g. post time, post count, etc.) will be helpful for identifying users with emotional disorders. Finally, a future avenue for 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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