Detecting Mental Disorders in Social Media Through Emotional Patterns - The case of Anorexia and Depression

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Abstract: Millions of individuals worldwide suffer from one or more mental illnesses that impact how they think and act. Although difficult, early detection of these problems is essential because it may allow for assistance to be given to patients before their condition worsens. Monitoring how individuals express themselves, such as what and how they write or go one step further, what emotions they exhibit in their social media conversations, is one way to do this. In this work, we examine two computer models that are designed to simulate the occurrence and evolution of emotions reported by social media users. Two recent public data sets for two significant mental disorders—depression and anorexia—are used in our review. The findings obtained imply that the presence and variety of emotions, captured by the suggested representations, enable the identification of significant information about social media users who are anorexic or depressed. Additionally, combining the two representations can improve performance, putting it on par with the best reported method for treating depression and only 1% behind the best method for treating anorexia. Additionally, these representations give the results the potential to gain some interpretability.

1. INTRODUCTION

Different interferences with thinking and behaviour are brought on by a mental disorder [1]. These disruptions, which may range in severity from moderate to severe, may make it difficult to go about everyday tasks and meet regular obligations [2]. Millions of individuals worldwide are impacted by common mental illnesses including anorexia and depression. They may be caused by a single occurrence that caused the sufferer extreme stress or by a string of stressful incidents. It is also common knowledge that nations that often experience either widespread violence or natural catastrophes see a rise in mental problems. For instance, a study of mental diseases in Mexico conducted in 2018 found that 17% of the country's population had at least one mental problem and that one in four people would have a mental disorder at some point in their lives [3]. In a similar spirit, we take it for granted that social interaction may take place in the real world as well as the virtual one produced by social media websites like Facebook, Twitter, Reddit, and others. This fact offers both significant potential and certain obstacles that, if properly handled, might advance our knowledge of what and how humans communicate. This study's objective is to analyse social media documents 1 using automated emotional pattern recognition in order to find out if the local population has any symptoms of anorexia or depression [4]–[6]. Previous studies have focused on analysing social media users' emotions by examining their contrast and tone. According to these studies, the analysis of emotions in social media allows capturing crucial information related to users, and they have mainly applied this analysis to predict users' age and gender as well as a range of sensitive personal attributes including sexual orientation, religion, political orientation, income [9], and personality traits [10], [11]. This information gives us a chance to increase the use of emotions in the social media identification of anorexia and depression.

A Description Of The Project: The two hypotheses that serve as inspiration for the proposed static and dynamic representations, BoSE and -BoSE, respectively. The first is that terms associated with strong emotions in lexicons are unable to convey small emotional distinctions, which in reality provide the most valuable information about a user's mental health. For instance, terms like furious, angry, and disturbed that denote varying degrees of fury are included in the lexicon linked with the anger emotion even if they are connected with the same emotion. Therefore, our suggestion is to use a histogram of subemotions to represent each user. These subemotions are found by clustering word embeddings within coarse emotions. The second theory is that depressed and anorexic individuals exhibit more emotional turbulence than typically healthy individuals. In this instance, the goal is to represent each user using a collection of statistical numbers that illustrate how often the sub-emotions vary over time. The following are the contributions of this research for identifying those with depression or anorexia based on these hypotheses:

1) We expand on the BoSE representation and suggest a new one based on sub-emotions to better capture the changing emotional states of social media users.

2) To enhance the identification of sadness, we provide a method that combines static and dynamic representations utilising early and late fusion procedures.

The usage of these representations based on fine-grained emotions is expanded for the job of detecting anorexia, and the emotional patterns that are identified are contrasted with those that were acquired from the task of detecting sadness.

2. LITERATURE SURVEY

2.1 Existing System

Depression is a mental health condition marked by a consistent lack of interest in things to do, which may significantly complicate daily living [1], [17]. Crowdsourcing has been the primary method employed by studies concentrating on the automated identification of this condition to gather information from users who explicitly have acknowledged receiving a clinical depression diagnosis [18], [19]. The most well-liked method among these research uses conventional classification algorithms and treats words and word n-grams as characteristics [13], [20], [21]. The primary goal is to record the most often used terms by people who are depressed and compare them to the most frequently used words by healthy users. This method fails because people with and without depression often have a wide range of words in common.

Using a LIWC-based representation, another group of studies [22] attempted to categorise user postings into a variety of psychologically significant categories, such as social ties, thought processes, or individual differences [18], [23]. These efforts have made it possible to characterise mental illness conditions more accurately, although the findings they produced were only marginally superior to those of using simply words. Recent studies have looked at ensemble approaches, which combine deep neural models like LSTM and CNN networks with word- and LIWC-based representations [24], [25]. In the eRisk- 2018 shared challenge on depression diagnosis, for instance, [25], [26] the combination of these models with factors including word frequencies, user-level linguistic information, and neural word embeddings provided the best-reported result.

These studies demonstrate that relevant information on whether a person has depression may be found in social media messages, however the findings are sometimes difficult to understand. This is a significant drawback since these technologies are naturally designed to assist healthcare practitioners rather than make choices. The authors perform research in [28]

[29] to address this issue. They define users who suffer from mental illnesses and provide techniques for visualising the data to give psychiatrists insightful information.[23-27]

2.2Proposed System

The two assumptions that serve as inspiration for the proposed static and dynamic representations, BoSE and _-BoSE, respectively. The first is that terms associated with strong emotions in lexicons are unable to convey small emotional distinctions, which in reality provide the most valuable information about a user's mental health. For instance, terms like furious, angry, and disturbed that denote varying degrees of fury are included in the lexicon linked with the anger emotion even if they are connected with the same emotion. Therefore, our suggestion is to use a histogram of sub emotions to represent each user. These sub emotions are found by grouping the word embeddings within coarse emotions. The second theory is that depressed and anorexic individuals exhibit more emotional turbulence than typically healthy individuals. The goal in this instance is to portray each user using a collection of statistical statistics that illustrate how often the sub-emotions vary over time.

2.3FINE-GRAINED EMOTIONS TO TEXTS

Humans experience emotions constantly, and they have been extensively researched in domains like psychology and neurology Particularly in psychology, a link between emotions and mental diseases has been shown, and study into how emotions show up in language via words is ongoing [14]. These findings help us understand how to assess emotions, or more specifically, subemotions, as a method to accurately diagnose anorexia and depression in Reddit users.

The suggested strategy for identifying anorexia and depression takes into account document representations based on the reported fine-grained emotions. First, we generate groups of fine-grained emotions (referred to as sub-emotions from this point forward) for each general emotion that is a part of the EmoLEX lexicon [23] in order to build these representations. This lexical resource shows the correlation between words and two negative and positive attitudes, as well as the eight emotions of anger, fear, anticipation, trust, surprise, sadness, joy, and disgust.

The words are accessible in 40 different languages and include handwritten annotations. The text is then hidden, and each document is then represented by labelling the sub-emotions in place of the original words. Each phase of this process was covered in depth in the sections that followed.

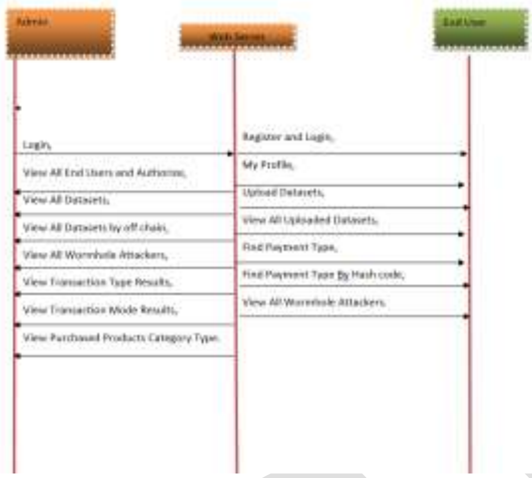

Fig 1: System Flow

3. SYSTEM ANALYSIS&DESIGN

3.1 Creating The Secondary Feelings

Formally, we denote the set of emotions in EmoLex as E = [E1, E2,..., E10], where Ei = [t1,.., tn] is the set of words denoting the emotions. Ei4 . Using Wikipedia pre-trained sub-word embeddings of size 300 from FastText [44], we construct a vector for each word in the lexical resource. We experimentally assessed the vector size taking into account choices of 100, 300, and 500 together with word2vec [24] and glove [25] word embeddings. We cluster the words using the Affinity Propagation (AP) technique, a graph-based clustering approach that is comparable to k-means but does not need predetermining the number of clusters. This is done after calculating the vectors for each word (from each coarse emotion). This technique looks for instances of input set members that are typical of clusters [47]. Each centroid reflects a separate sub-emotion after the clustering. This means that each emotion is now represented by a collection of sub-emotions, where each Sj is a subset of the words from Ei. A set S containing all calculated sub-emotions is produced by this technique.

3.2 Text to sub-emotion sequence conversion

In accordance with the protocol, we construct a single document for each user by concatenating all of their individual posts.

Then, we replace every user's word with a label that corresponds to the word's closest sub-emotion to mask all of their documents. For this, we construct prototype sub-emotion vectors by averaging (column-wise) word embeddings in each cluster after clustering word vectors of each coarse emotion. We count each word in text as an instance of a certain subemotion using these prototypes. Returning to Figure 2, for instance, the sub-emotion surprise2 is represented by the average of the column-wise presented vectors from the words art, museum, artwork, gallery, and visual. After obtaining these vectors, we compare each word's cosine similarity to each sub-emotion vector S and replace it with a label corresponding to that closest sub-emotion for each word t in the text sample.

3.3 System Architecture:A dynamic sub-emotion representation is ∆-BoSE.

This study's hypothesis is that users with anorexia and depression exhibit some variation in their emotional expression. Following this insight, we suggest a novel representation we call ∆-BoSE that may encapsulate temporal emotional patterns.

The post history of each user is first divided into n pieces or chunks6 in order to generate the ∆-BoSE representation. Then, as stated, we calculate the BoSE representation for each chunk. In other words, we see the pieces as separate but related texts. Following this procedure, a vector of n values, S i = hwi,1, ,wi,ni, is created for each of the m sub-emotions, where wi,j represents the weight of sub-emotion Si in chunk j as determined by Formula 2.

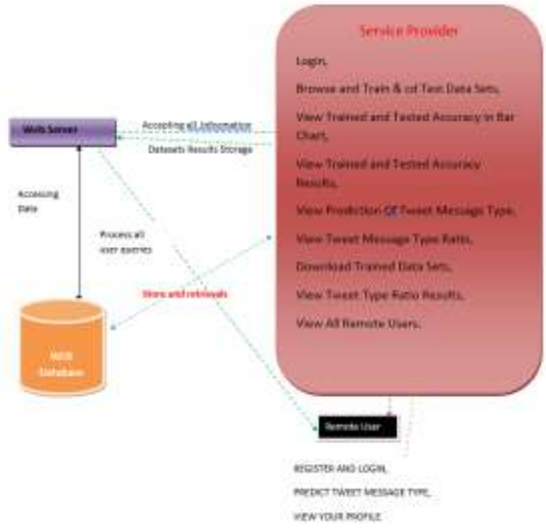

Fig 2 : System Architecture

3.4 Data Flow Diagram : Whenever a new system is developed, user training is required to educate them about the working of the system so that it can be put to efficient use by those for whom the system has been primarily designed. For this purpose the normal working of the project was demonstrated to the prospective users. Its working is easily understandable and since the expected users are people who have good knowledge of computers, the use of this system is very easy.

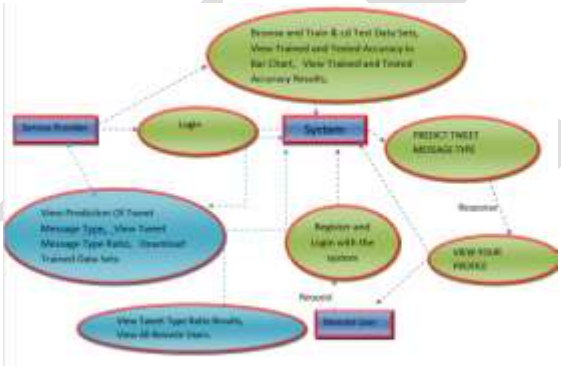

Fig 3: Data Flow Diagram

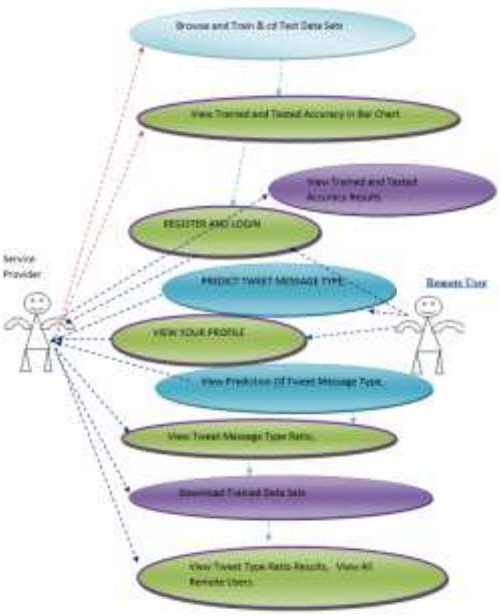

Fig 4 Use Case UML Diagrams

5. CONCLUSION

In this study, we demonstrated how representations based on fine-grained emotions might capture more particular subjects and difficulties that are conveyed in social media documents by users who, sadly, suffer from anorexia or depression. In other words, the automatically derived sub-emotions provide helpful data that aids in the identification of these two mental diseases. On the one hand, the BoSE representation outperformed the suggested baselines, including certain deep learning techniques, and enhanced the outcomes of employing merely general emotions as features. On the other hand, the addition of a dynamic analysis of the sub-emotions, known as ∆-BoSE, increased the identification of users who exhibit symptoms of anorexia and depression, demonstrating the value of taking into account how the sub-emotions vary over time. It is important to note the clarity and interpretability of both representations before constructing a more simple analysis of the outcomes. Last but not least, the capacity to predict users' emotional behaviour using their social media data offers a chance for future wellness-promoting devices. This kind of technology may act as early warning systems that provide regional analysis and details about a mental condition while preserving user privacy. The authorities may opt to provide professional aid or emotional support, which the users may choose to accept or reject, based on this information, which may also include the existence of mental problems in certain regions. We think it's crucial to point out that when we examine social media stuff, we could be concerned about people's privacy or have some ethical reservations. Given the users' individual behaviour and mental state, these risks arise from the utilisation of information that may be sensitive. The experiments and use of this data are solely for study and analysis; it is not permitted to abuse or handle the data in any other way.

6. FUTURE SCOPE

Although the effectiveness of emotion fusion in identifying mental illnesses has been amply demonstrated in this review, there are still a number of difficulties. This section outlines some of the most significant obstacles to diagnosing mental illness as well as possible future research options.We urge researchers to publish their datasets and source code to address the aforementioned issues while also taking into account moral obligations to preserve privacy and prevent psychological harm. Additionally, Table 4's 38 datasets show that the most common types of mental illnesses are depression (42%) and suicide (24%), followed by other mental disorders (34%). In order to address future needs for mental health applications, it is important to promote the creation of various mental disease detection databases (such as those for anorexia and bipolar disorder). In order to further enable the testing and analysis of emotion fusion algorithms, more mental illness detection datasets with emotion labels should be developed. When the number of annotated datasets is inadequate to allow fully supervised learning, semi-supervised, and weakly supervised approaches may also be used.

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