TRACKING MENTAL DISORDERS ACROSS TWITTER USERS

by

SAYALI SHASHIKANT KALE

(Under the Direction of I. Budak Arpinar)

ABSTRACT

The prevalence of mental health disorders is often undetected, leading to a serious issue which continues to affect all parts of society. Recurrent psychological patterns can be identified with the help of popular social networking websites. These patterns can depict one’s thoughts and feelings in everyday life. Our research targets Twitter data to identify users who could potentially suffer from mental disorders, and classify them based on the intensity of linguistic usage and different behavioral features using sentiment analysis techniques. To confront the growing problem of mental disorders, we demonstrate a novel approach for the extraction of data and focus on the analysis of depression, schizophrenia, anxiety disorders, drug abuse and seasonal affective disorders. Our system can be used not only to identify, but also to quantify users' progression by following them on Twitter for a certain period of time. This can eventually help medical professionals and public health experts to monitor symptoms and progression patterns of mental disorders in social media users.

INDEX WORDS: Twitter, Sentiment Analysis, Mental Health, Data Extraction

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SAYALI SHASHIKANT KALE

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SAYALI SHASHIKANT KALE

Major Professor: I. Budak Arpinar
Committee: Thiab R. Taha
Khaled Rasheed

Electronic Version Approved:

Suzanne Barbour
Dean of the Graduate School
The University of Georgia
December 2015

DEDICATION

I would like to dedicate this Thesis to my parents, sister and all my family members for their constant support and encouragement.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Mental disorders have become a serious issue all over the world. Centers for Disease Control and Prevention (CDC) estimated that "by the year 2020, depression will be the second leading cause of disability throughout the world" (CDC, 2013). Mental disorders can even lead to substance abuse, violence and suicide. The majority of people with mental disorders often go undiagnosed and untreated. So there is a need to diagnose and treat such kind of disease.

The social media can be used as a diagnostic tool to study psychology of a person. Social networking websites such as Twitter depicts ones mental state. Following is a snapshot from Twitter which picturizes emotional state of a person.

Figure 1: Twitter snapshot

The goal was to analyze such kind of writings from Twitter. Tweets were extracted using keywords related to mental health, signs, and symptoms of 5 different mental disorders. We extracted 10 million of tweets using 40 different keywords over a period of 6 months and classified them into two classes relevant as most, moderate or least and irrelevant. After this, we followed 200 users for 2-3 months duration to check their activities.

1.2 Mental Disorders Studied

National Alliance of Mental Health (NAMI) states that "a mental illness is a condition that impacts a person's thinking, feeling or mood may affect and his or her ability to relate to others and function on a daily basis" (NAMI, 2015). Depression and schizophrenia are the most common types of mental illnesses in the world.

"Mental health disorders such as depression are among the 20 leading causes of disability worldwide**.** Depression affects around 300 million people worldwide and this number is projected to increase. Fewer than half of those people affected have access to adequate treatment and health care" (WHO, 2015).

Following are the types of mental disorders as per WebMD: anxiety disorders, mood disorders, psychotic disorders, eating disorders, addiction disorders, personality disorders, obsessive compulsive disorders (OCD), Post-traumatic Stress disorders (PTSD) etc. We will be focusing on following major disorders below. WebMD (WebMD, 2015a) provides definitions of these disorders as follows:

Anxiety Disorders:

“People with anxiety disorders respond to certain objects or situations with fear and dread, as well as with physical signs of anxiety or panic, such as a rapid heartbeat and sweating. It includes generalized anxiety disorder, panic disorder, social anxiety disorder and specific phobias.”

Mood Disorders/ Affective Disorders:

“It involves persistent feelings of sadness or periods of feeling overly happy, or fluctuations from extreme happiness to extreme sadness. The most common mood disorders are depression, bipolar disorder, and cyclothymic disorder. Depression includes major depression, persistent depression, seasonal affective depression which is caused due to change in the season, psychotic depression etc.”

Psychotic Disorders:

“Psychotic disorders involve distorted awareness and thinking. Two of the most common symptoms of psychotic disorders are hallucinations – the experience of images or sounds that are not real, such as hearing voices – and delusions, which are false fixed beliefs that the ill person accepts as true, despite evidence to the contrary. Schizophrenia is an example of a psychotic disorder.”

In Chapter 2 we will look at the background of sentiment analysis and emotion analysis. Chapter 3 talks about problem statement, ontology creation and its uses. Chapter 4 describes detailed architecture of the system. Then Chapter 5 represents results and evaluation procedure followed by Chapter 6 as related work and then Chapter 7 is the conclusion and future scope of the project.

1.3 Contribution to the Field

Social media is a vast source of information by real people in real time. In recent years, because of social networking, people express their inner feelings on the web.
This could help us in the early identification of different disorders by looking at their writings and analyzing it. This paper contributes to the field of public health by providing a platform to find emotionally distressed people, who could potentially suffer from different mental diseases.

In this study, we extracted tweets from Twitter using different keywords related to mental disorders. We seek to identify potentially mentally ill users and follow their activities over a period of time. Also we plan to separate them into different classes based on the intensity of tweets. Another major goal of the study is to find the seasonal pattern of seasonal affective disorder over a period of eight months. We try to bridge the gap between results from clinical studies and results from social media. The overall goal is to observe psychologically proven facts from social media. Our research contributes to this novel approach by building our own domain specific dictionary. Over time, it can evolve into ontology for the field of mental disorders which can help to identify sentiments and emotions more accurately.

1.4 Broader Impact:

Our research will impact the diagnosis, and eventually the treatment, of a range of different mental disorders in society. Our system will help to track mental disorders such as depression, schizophrenia, anxiety disorders, drug abuse and seasonal affective disorders on Twitter. The method we developed will analyze the tweets related to a domain, and then it will filter the users who potentially could have severe signs of mental disorders. Then it tracks the activities of those users over a period of time on Twitter. This will benefit psychologists or public health experts to filter out relevant data by using our system and then to study the symptoms and progression patterns of those users before it turns into a severe problem. Eventually, medical professionals can use this relevant data as a sample data for clinical analysis of mental disorders.

CHAPTER 2

BACKGROUND

2.1 Social Media

Social media plays vital role in the information gathering and making sense out of the data. Kwak et. Al says that “Twitter is an ideal example of a micro blogging website which is fast growing; it connects millions of users with their tweets, which is nothing but a text. Users can write about any topic within the 140 characters limit and also follow other users on twitter to get an updates from them” (Kwak, Lee, Park, & Moon, 2010). Mental illness affects a person’s intelligence, emotions, and day to day activities.

These days scientists are interested in analyzing big social media data for mental disorder cases such as anxiety, bipolar disorders, depression, dissociative disorders, eating disorders, obsessive-compulsive disorders, post traumatic disorders, drug abuse, seasonal affective disorders etc. The goal is to find potential users suffering from mental illness from Twitter and analyze their activities over a period of time to find certain patterns.

In this section, we try to investigate different research papers related to mental disorders and social media like Twitter, and Facebook in order to study how social media is closely related to real life. “Johns Hopkins computer scientists have already evaluated Twitter posts for tracking flu cases. They say by careful consideration of tweets, it is possible to link data to different disorders” (JHU, 2014). User’s tweets or retweets reflect their emotional and mental state when they are suffering from mental illness. Sometimes users also post about their mental condition socially. Facebook, which is another microblogging website, has this kind of an option. Whenever a user is posting, it asks for: what's on your mind? How are you feeling, thinking about, eating, watching etc.? Where are you? So, from this information, it is easy to conclude that certain behavior or pattern of a person which could be linked to mental conditions. Therefore in this section, we study how user's moods are captured from different social networking websites and are linked to mental disorder cases using sentiment analysis techniques.

2.2 Sentiment Analysis

Tejwani, who conducted a survey on sentiment analysis, states that "Sentiment analysis is also known as opinion mining in which text analysis, natural language processing techniques are used to identify sentiments "(Tejwani, 2014). This survey covered different techniques used in sentiment analysis and opinion mining. It states, "Sentiment classification classifies text as per different opinions towards certain object. Feature based sentiment classification considers the opinions on features of certain objects" (Tejwani, 2014). The sentiment analysis task is classified into three different levels: document level, sentence level, and feature bases techniques i.e. aspect level and comparative analysis (Liu, 2010).

There are different methods used in classification of texts. Most of them are based on word and phrase classification. Dictionary based approach is commonly used in general. Also machine-learning approach is very commonly used in which data are trained on specific data set and then tested on different datasets. Commonly used machine-learning techniques are Naïve Bayesian, Support Vector Machine and Maximum Entropy. It depends on how well features are being extracted from the dataset. Features might be unigrams, bigrams, parts of speech tagging, emoticons detection, categories tagging etc. (Tejwani, 2014). In dictionary based or corpus based approach, ‘Word Net’ a bag of words which could be domain specific is used to classify sentiments and opinion extraction.

2.3 SMART Sentiment and Emotion Analysis

SMART is a tool named Social Media Analysis in Real Time. This section describes details of SMART. Identification of exact emotions is the most crucial step in a sentiment analysis technique. Psychologist Robert Plutchik defined there are basic eight human emotions and he created Plutchik’s wheel of emotions to demonstrate his theory (Plutchik, 2001). Plutchik's eight basic emotions are *joy*, *trust*, *fear*, *surprise*, *sadness*, *anticipation*, *anger*, and *disgust*. Middle ring in the wheel represents primary emotions and each has an opposite such that joy is the opposite of sadness, fear is the opposite of anger, anticipation is the opposite of surprise and disgust is the opposite of trust. Toward the wheel’s center, intensity of emotions increases and it decreases as we move outwards in the wheel. The color indicates intensity, so emotion is more intensive with the darker shade of the color.

For example, sadness at its least level of intensity is pensiveness and at its highest level of intensity, anger becomes grief. So this demonstrates relationships between emotions

(Plutchik, 2001). An automatic emotions detection system such as NRC Emotion Lexicon (Mohammad & Turney, 2013) uses a Plutchik's wheel of emotions to express emotion categories.

Plutchik's wheel of emotion has many applications in the field of sentiment analysis techniques. It is used in social media analysis, text analysis, which finds polarity (positive or negative) of the sentence and intensity of emotions.

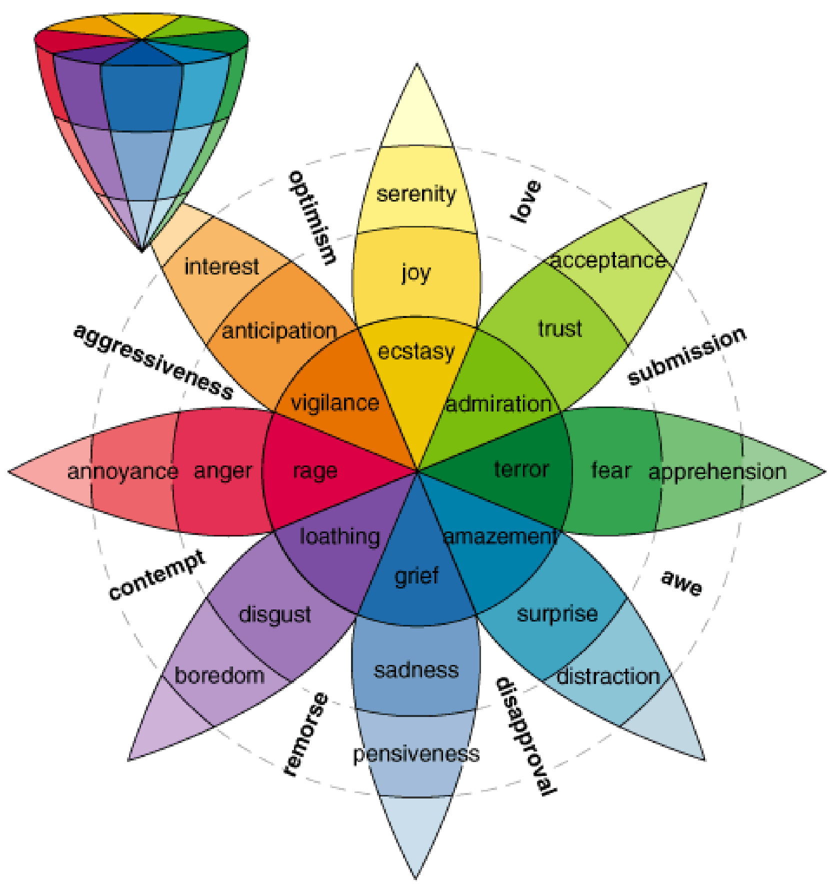


Figure 2: Plutchik's Wheel of Emotions

(Plutchik, 2001)

We can see that the emotions, sadness and surprise together represents disapproval whose opposite is optimism and so on which gives us a possibility of 32 classes to classify the emotions (Plutchik, 2001).

In (Desai, 2014) SMART- SEA project, emotions are classified on a scale of 0-5. Zero indicates there are no emotions present in the tweet and 5 represent most intense emotion. If the emotion score is 1-2 then it falls under the outermost ring of the Plutchik's wheel, which exists serenity, acceptance, apprehension, distraction, pensiveness, boredom, annoyance and interest. If the score is 3-4 then the emotion falls in the middle ring of the Plutchik's wheel which represents joy, trust, fear, surprise, sadness, disgust, anger and anticipation. And if the score is 5, then it falls in the innermost ring which has emotions such as ecstasy, admiration, terror, amazement, grief, loathing, anger and vigilance.
As mentioned above, 32 combinations are difficult for the analysis and also it could be overwhelming for an annotator; therefore, SMART considered only a middle ring of emotions for the analysis and annotated wordlist on the basis of joy, trust, fear, surprise, sadness, disgust, anger and anticipation.

We observed that along with SMART wordlists and NRC, there were no domain specific words or phrases that are most commonly used on social media, which we observed in tweets. So, we created our own domain specific dictionary by making use of existing wordlists. Section 3.2 talks about how we created this word dictionary and ontology.

CHAPTER 3

MENTAL DISORDER ANALYSIS

3.1 Problem Statement

In recent years, cases involving depression and drug abuse are very serious. A mental disorder could be life threatening. We often hear in the news that, a person committed suicide, killed people under mental stress, was drunk and driving and had an accident etc. Then after few days it is revealed in the news, the person was depressed or mentally abnormal. If we observe certain peoples profile on Twitter before the event has occurred, it could lead to the conclusion that, their writings show some kind of distress or negativity in their life, which could be the clue for identifying mental disorder.

It is difficult to identify exact mental disorder symptoms just by studying a few tweets, as they are not always obvious. This was the motivation behind our approach. Considering the significance of the problem, there is a need to offer a flexible platform to analyze emotions and mental condition of a person over a period of time.

Thus, we seek to contribute to the public mental health analysis by providing a platform that will identify a person who could potentially suffer from mental disorders. This could also help to identify potential suicidal victims as usually it is due to their mental imbalance.

3.2 Dictionary Creation

We built a domain specific dictionary using three approaches, namely existing wordlists, word count frequency and POS tagging.

3.2.1 Using Existing Wordlists

Dictionary creation or building of the wordlist was a very crucial step in our project. There are numerous wordlists already built for the sentiment analysis and opinion mining in various domains. SentiWordNet 3.0 is one of the wordlists built for sentiment analysis. It is freely available for non-profit research purposes. It has *positive score*, *negative score*, *objective score* and *synonyms* of a word. We considered all the words and their synonyms with negative scores (Baccianella, Esuli, & Sebastiani, 2010). Similarly, we added more unique words from AFINN wordlist, which is a bag of words with *positive* and *negative valence* ranging between -5 to +5. It has 2477 words and phrases. We considered all the negative words irrespective of its range (Nielsen, 2010). Followed by this, we examined National Research Council of Canada (NRC) wordlist created by Saif Mohammad (Mohammad & Turney, 2013). NRC emotion lexicon has two sentiments as positive and negative along with eight different emotions. We added unique words with negative sentiments which were already not present in our final wordlist. There was also an emotional vocabulary list by Karla McLaren, which has specifically words related to depression, suicide and anxiety etc.(McLaren, 2015) But, there was no domain specific wordlist created till now, so there was a scope for the improvement in these wordlists with domain specific words, i.e., words specifically related to mental health and disorders. So this leads to the creation of our own wordlist named Twitter Mental Disorders wordlist.

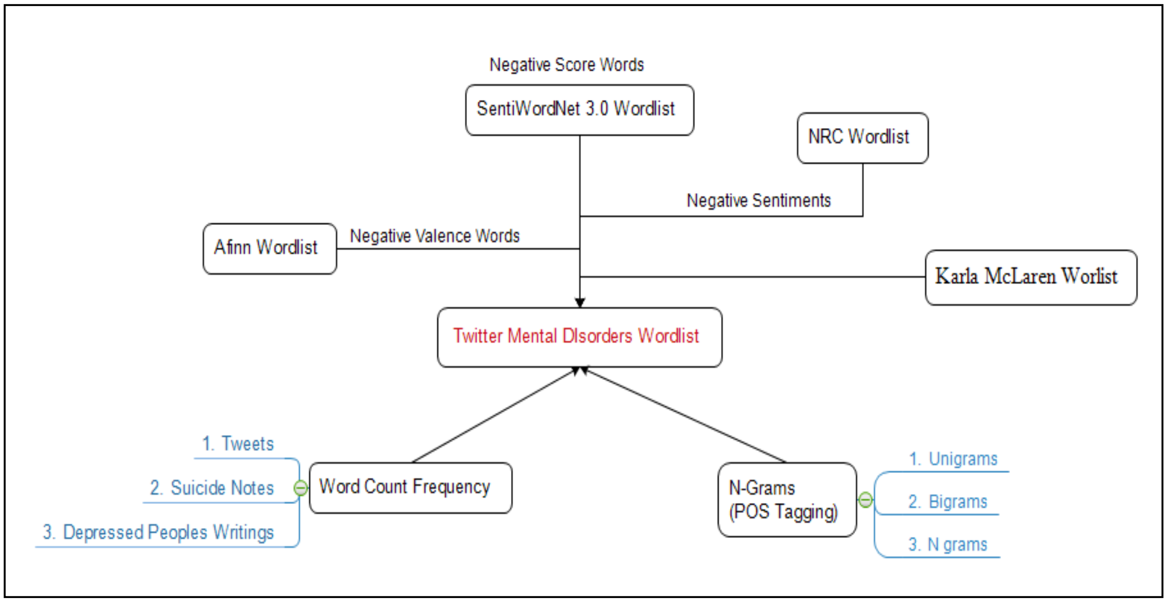


Figure 3: Twitter Mental Disorders Wordlist

3.2.2 Word Count Frequency

We considered few thousand sample tweets for wordlist creation. Tweets were extracted using different keywords related to the domain. Those tweets were considered as our training data set. Using word count frequency concept, words were organized in descending order of frequency count. We considered maximum occurring relevant words specific to our domain of mental disease and mental health and then added to our dictionary. Similarly, using this technique, we evaluated a few suicide notes and depressed people's writings online. Since mental health has become a serious issue all over the world, there are many active blogs related to this domain.[1] These blogs are targeted to those audiences who are suffering from mental illnesses.

We then targeted many psychological papers dealing with mental health. We found scientific words related to mental diseases, which are not commonly known by ordinary people. But we added those words so as to improve the accuracy of the system. Mainly we looked into the "Diagnostic and Statistical Manual of Mental Disorders (Fifth Edition)" by American Psychiatric Association (APA, 2014). There are different surveys/questionnaires in order to identify and better treat mental disorders. Furthermore, CDC and NAMI have many clinical surveys. We analyzed those questions in the surveys for better wordlist creation.

Finally, we utilized ontology of diseases created by Institute for Genome Sciences-University of Maryland School of Medicine (Medicine, 2015). We updated mental health section with a few more attributes in it along with symptoms and used this for our dictionary creation.

3.2.3 POS Tagging

First we used Porter Stemmer Algorithm to normalize the words and make it more meaningful in terms of sentiments (Porter, 1980). We then used Stanford's Parts of Speech Tagger (POS) (Stanford) to tokenize all the words in a given sentence using

[1] www.MentalHealth.gov, https://www.pinterest.com/bipolarbandit/blogs-about-mental-illness-mental-health and http://lets-beat-mental-illness.tumblr.com/

certain rules mentioned by Turney and we added our own rules to it (Turney, 2002). We mainly removed nouns/proper nouns or verb followed by noun from the dataset.

For example, consider this tweet: “I am feeling low because of this depression”. In this we get, VB is feeling, adjective is low so “feeling low” as bigram and “depression” as NN.

Consider a second example: “I hate myself”. In this tweet, we get Hate as VB and myself as NN so bigram is “hate myself” etc.

We then evaluated all extracted n grams if they are domain specific, otherwise we removed irrelevant words from the list. We observed, most of the n grams have been already present in above wordlist, but we wanted to check this for more accurate results. So, by considering all these approaches, use of existing wordlists, word count frequency and POS tagging, the wordlist size was almost 2,000 words related to mental health and diseases.

CHAPTER 4

Architecture

Here is our high level system architecture diagram:

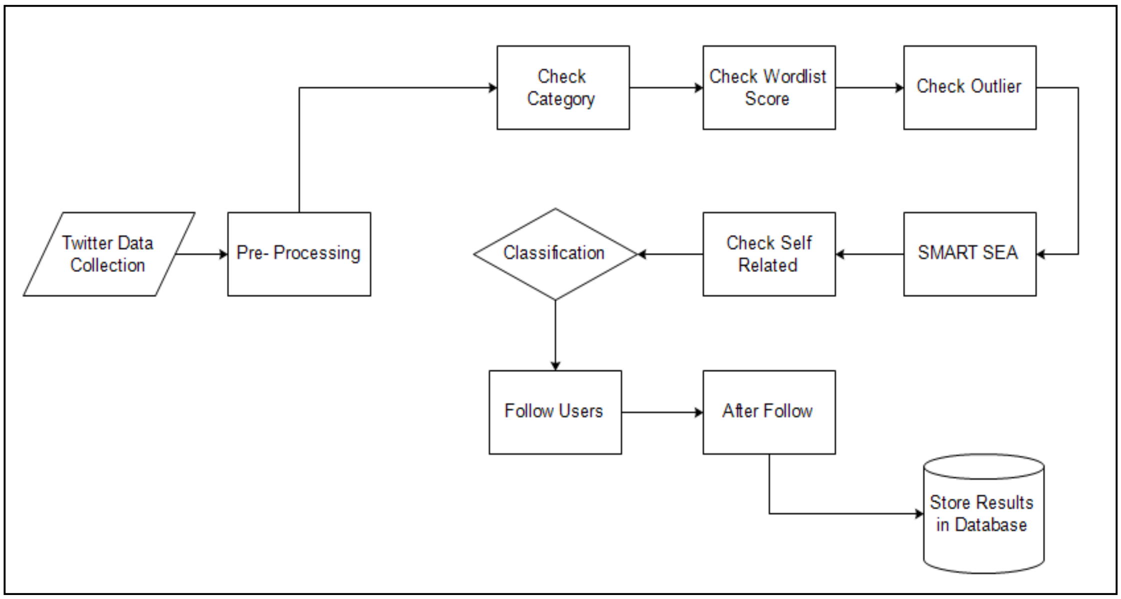


Figure 4: High Level System Architecture

4.1 Data Collection

Twitter is a fast growing microblogging website. Millions of people share their thoughts publicly. The short text message is known as a tweet, which is a max 140 characters in length. The hashtag is a common pound (#) symbol which is used to describe particular interest or group on social networking website. So, Twitter data were our main target for further analysis. We extracted almost 10 million tweets over a period of 6 months. Twitter provides two API's for the extraction of data, REST and Streaming. Rest API is used to access previous tweets of users, whereas the Streaming API allows one to access tweets in real time based on a certain query. We used Streaming API to access tweets in real time manner based on hashtags, users etc. For this purpose, Twitter provides OAuth to access this APIs. First, user needs to create a Twitter application and then generate a consumer key, a consumer secret key, an access token and an access token secret key, which enable users to access the Twitter API on behalf of them (Twitter, 2015).

Our system is designed using Python programming language. Tweepy which is an open source package is used to extract tweets from Twitter. It allows Python to use Twitter APIs to access tweets (Roesslein, 2009).

Following is a diagrammatic representation of data extraction process:

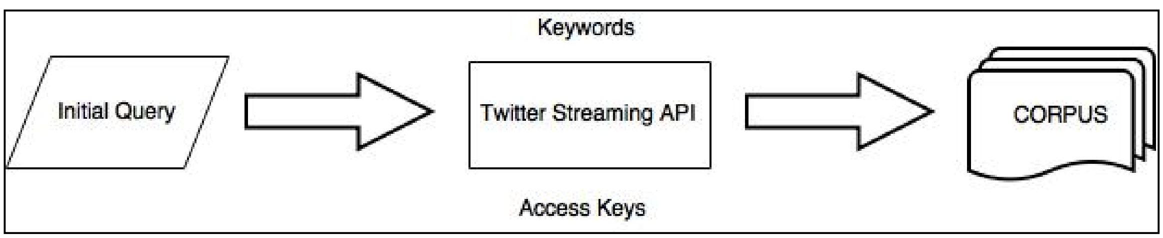


Figure 5: Data Extraction

Initial Query is to start initial streaming process using Twitter API. Twitter streaming API initiates the process of data extraction using certain keywords and access keys. Corpus is nothing but tweets, which are stored in JSON format (Twitter, 2015).

We used around 40 different keywords or phrases to extract the data. Keywords are as follows: *depression, schizophrenia, bipolar, suicide, suicidal, nervous, depress, depressing, distress, dejected, dejection, gloomy, cheerless, blue, empty, sad, insomnia, feeling low, hate myself, kill myself, don't want to live anymore, ashamed of myself, ashamed of myself, heat broken, feelings of worthlessness/guilt, lonely, loneliness, winter* *depression, SAD, seasonal affective disorders, antidepressants, pills for depression, bipolar disorder, pristiq, cymbalta, vilazodone, social anxiety, anxiety, worried, hopeless, despair* etc.

Based on these keywords, we segregated tweets into 4 different categories for further evaluation of tweets.

Categories are as follows: 1) Depression, 2) Schizophrenia, 3) Anxiety Disorders and 4) Seasonal Affective Disorders (SAD).

4.2 Pre-Processing

Extracted tweets were in JSON format. We filtered few objects from the JSON format such as Tweet Text, Created at (Date and Time), Location and Username.


```
{"created_at":"Tue Jul 21 20:17:30 +0000 2015","id":623587624566005760,"id_str":"623587624566005760","text":"SUMMERTIME SADNESS",
"source":"\u003ca href=\"http:\/\/twitter.com\/download\/android\" rel=\"nofollow\"\u003eTwitter for Android\u003c\/a\u003e",
"truncated":false,"in_reply_to_status_id":null,"in_reply_to_status_id_str":null,"in_reply_to_user_id":null,"in_reply_to_user_id_str"
"in_reply_to_screen_name":null,"user":{"id":2352338215,"id_str":"2352338215","name":"bel","screen_name":"borntocall4te",
"location":"en la kaye","url":null,"description":"siempre piola","protected":false,"verified":false,"followers_count":418,
"friends_count":444,"listed_count":0,"favourites_count":2033,"statuses_count":1883,"created_at":"Wed Feb 19 22:30:57 +0000 2014",
"utc_offset":-10800,"time_zone":"Brasilia","geo_enabled":false,"lang":"es","contributors_enabled":false,"is_translator":false,
"profile_background_color":"ABB8C2","profile_background_image_url":
"http:\/\/pbs.twimg.com\/profile_background_images\/599683184905719808\/nZGC4vXP.jpg",
"profile_background_image_url_https":"https:\/\/pbs.twimg.com\/profile_background_images\/599683184905719808\/nZGC4vXP.jpg",
"profile_background_tile":true,"profile_link_color":"000000","profile_sidebar_border_color":"FFFFFF",
"profile_sidebar_fill_color":"DDEEF6","profile_text_color":"333333","profile_use_background_image":true,
"profile_image_url":"http:\/\/pbs.twimg.com\/profile_images\/622066392888647680\/NyWNKeff_normal.jpg",
"profile_image_url_https":"https:\/\/pbs.twimg.com\/profile_images\/622066392888647680\/NyWNKeff_normal.jpg",
"default_profile":false,"default_profile_image":false,"following":null,"follow_request_sent":null,"notifications":null},
"geo":null,"coordinates":null,"place":null,"contributors":null,"retweet_count":0,"favorite_count":0,"entities":{"hashtags":[],
"trends":[],"urls":[],"user_mentions":[],"symbols":[]},"favorited":false,"retweeted":false,
"possibly_sensitive":false,"filter_level":"low","lang":"en","timestamp_ms":"1437509850051"}
```


Figure 6: Tweet in JSON Format

We then removed hashtag # followed by RT@ and @ symbols. Regular expressions, special characters were also removed. We also removed http:// and the following web address from the text. All the tweets were then turned to lowercase letters. Specifically, we replaced following symbols/text with blank spaces:

1) Remove text which starts from http[^\\s]+
2) Remove hashtag #, @, RT@
3) Remove Unicode characters /([\ud800-\udbff][\udc00-\udfff])|./g
4) Convert to lowercase
5) Remove hyperlinks

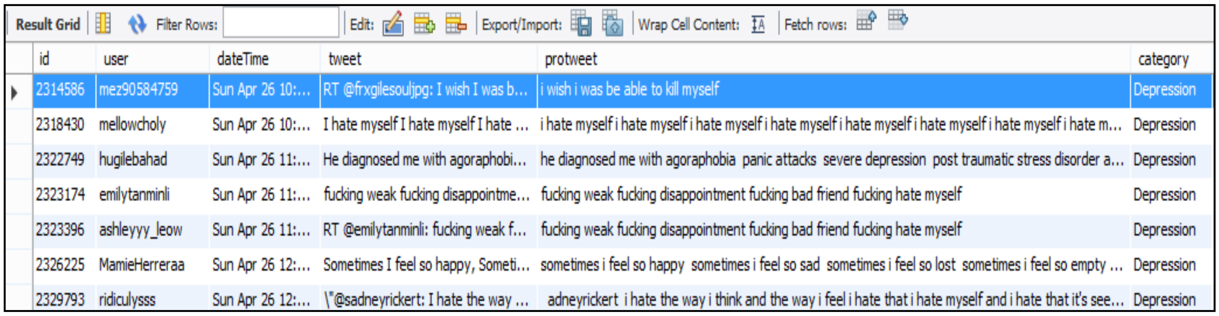
We did not remove Retweets, since it could be very useful in our analysis. Retweet is, when the user wants to repost someone else's tweet, she/he simply retweets. So, a user might feel the same thing as the other person. This could play an important contribution towards our study. Preprocessing and cleaning of the text also plays very significant role, since it removes all the inconsistency and irrelevant data from the text, which could lead to false results. Pre-Processed tweets are then compared with corresponding wordlists for further processing.

4.3 Check Category

There are different types of mental disorders, but it was not practically possible to study all. So we confined our study to the following 5 different categories:

1) Depression, 2) Schizophrenia, 3) Anxiety Disorders, 4) Drug Abuse and
5) Seasonal Affective Disorders (SAD).

We categorized tweets according to the keywords from which tweets were extracted. Different sets of keywords are related to above mentioned disorders.



Result Grid | Filter Rows: | Edit: | Export/Import: | Wrap Cell Content: | Fetch rows:

id	user	dateTime	tweet	protweet	category
2314586	mez90584759	Sun Apr 26 10:...	RT @frxgilesouljpg: I wish I was b...	i wish i was be able to kill myself	Depression
2318430	mellowcholy	Sun Apr 26 10:...	I hate myself I hate myself I hate ...	i hate myself i hate myself i hate myself i hate myself i hate myself i hate myself i hate myself i hate m...	Depression
2322749	hugilebahad	Sun Apr 26 11:...	He diagnosed me with agoraphobi...	he diagnosed me with agoraphobia panic attacks severe depression post traumatic stress disorder a...	Depression
2323174	emilytanminli	Sun Apr 26 11:...	fucking weak fucking disappointme...	fucking weak fucking disappointment fucking bad friend fucking hate myself	Depression
2323396	ashleyyy_leow	Sun Apr 26 11:...	RT @emilytanminli: fucking weak f...	fucking weak fucking disappointment fucking bad friend fucking hate myself	Depression
2326225	MamieHerreraa	Sun Apr 26 12:...	Sometimes I feel so happy, Someti...	sometimes i feel so happy sometimes i feel so sad sometimes i feel so lost sometimes i feel so empty ...	Depression
2329793	ridiculysss	Sun Apr 26 12:...	\"@sadneyrickert: I hate the way ...	adneyrickert i hate the way i think and the way i feel i hate that i hate myself and i hate that it's see...	Depression

Figure 7: Check Category of the Tweet

4.4 Check Wordlist

We checked if a word is present in SentiWord Net's negative bag of words. If it is not present, then we checked in Affin wordlist, if not then in NRC wordlist. But, this is very time consuming. So, we designed a better approach to improve time complexity of the system.

As discussed in wordlist creation section, we combined all domain specific words together into a single wordlist and built ontology based on relationships between entities. We check if a given word or phrase is present in our unique bag of words. When the word match is found, score is incremented by 1. So, we check all the words present in the tweet against this wordlists and get the score of the tweet.

For example, consider this tweet:

Tweet: "*insomnia depression and i hate people my life is turning for the worse at too young an age*"
Mental Disorder (MD) Score: 5
Matched words: *insomnia, depression, hate, life and worse.*

Result Grid | Filter Rows: | Edit: | Export/Import: | Wrap Cell Content: | Fetch rows:

id	user	dateTime	tweet	protweet	category	Score
2314586	mez90584759	Sun Apr 26 10:...	RT @frxgilesouljpg: I wish I was b...	i wish i was be able to kill myself	Depression	1
2318430	mellowcholy	Sun Apr 26 10:...	I hate myself I hate myself I hate ...	i hate myself i hate myself i hate myself i hate myself i hate myself i hate myself i hate myself i hate m...	Depression	10
2322749	hugilebahad	Sun Apr 26 11:...	He diagnosed me with agoraphobi...	he diagnosed me with agoraphobia panic attacks severe depression post traumatic stress disorder a...	Depression	10
2323174	emilytanminli	Sun Apr 26 11:...	fucking weak fucking disappointme...	fucking weak fucking disappointment fucking bad friend fucking hate myself	Depression	8
2323396	ashleyyy_leow	Sun Apr 26 11:...	RT @emilytanminli: fucking weak f...	fucking weak fucking disappointment fucking bad friend fucking hate myself	Depression	8
2326225	MamieHerreraa	Sun Apr 26 12:...	Sometimes I feel so happy, Someti...	sometimes i feel so happy sometimes i feel so sad sometimes i feel so lost sometimes i feel so empty ...	Depression	8
2329793	ridiculysss	Sun Apr 26 12:...	\"@sadneyrickert: I hate the way ...	adneyrickert i hate the way i think and the way i feel i hate that i hate myself and i hate that it's see...	Depression	8

Figure 8: Check Tweet Score

4.5 Check Outlier

Now, tweet score ranges from 0 to max 26. So, we observed tweets with maximum score, and we found, users have written 26 *hate* words in the tweet. There were many such tweets which were giving highest scores. Since, our interest has been to find a perfect range from the dataset, so that we can use that in our decision tree for further classification. If we consider these extreme scores, it will give incorrect results at the time of dividing the range. So, we decided to find outliers from the dataset.

Consider following dataset: 6, 4, 2, 1, 15, 0, and 0

1: Arrange in increasing order: 0, 0, 1, 2, 4, 6 and 15

2: Find Median of the dataset: 2

3. Find Quartile 1 and Quartile 3: 0 and 6

4. Find Interquartile: Q3- Q1: 6

5. Outlier is: Q3+ (1.5) Q1= 15

So in the above example, we neglect all the scores above 15. Since most of the tweets score is between 0 and 6, we can divide range equally. Outliers are considered to be extreme cases, so we can avoid them for better accuracy.

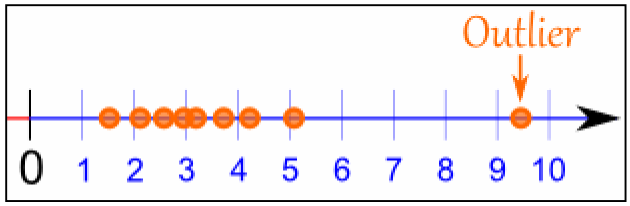


Figure 9: Outlier

(MathsIsFun.com, 2014)

Followed by this step, we used some part of SMART SEA project in our domain as explained below.

4.6 SMART SEA

LSDIS UGA lab conducted research in sentiment analysis using social media data under the direction of Dr. Budak Arpinar. SMART stands for 'Social Media Analysis in Real Time'. A graduate student from our lab Sanmit Desai (Desai, 2014) worked on this project by presenting his work named SEA that's 'Sentiment Analysis and Emotion Analysis'. For a better analysis in our project, we have used a part of his implementation and extended further. He analyzed a Twitter data for emotions in the context of social conflicts. In the current approaches, emotion dictionaries did not have any weights, lack of emoticons and no word list for domain specific. He contributed in the following areas:

- Improved Accuracy than National Research Council Canada Emotion Analyzer
- Assigned emotion weights, valence shifter and intensifiers.
- Bag of words specifically created for social conflict data (Desai, 2014).

The architecture consists of major 3 steps as loading wordlist, emotion labelling and valence shifter and intensifiers. The main approach is, given a word, check the context of the word, look for the word in the wordlist, assign emotion label, and assign weights and finally calculate emotion and sentiment weight. He created a SMART wordlist consisting of 1468 annotated words related to social conflicts. Although NRC wordlist has 35,000 words and SentiWordNet has 117,658 words, they were really not suited for domain specific analysis. So they created own wordlist for better accuracy and annotated all those words manually. SMART has bigrams, emotion weights, emoticons etc (Desai, 2014).

4.6.1 SMART Architecture:

4.6.1.1 Loading WordLists

SMART has three wordlists namely SMART wordlist which has sentiment score from -5 to +5 range followed by 8 emotions ranges from 0 to +5. For NRC, sentiment values are 0, -1 and 1 and emotions will be 1 or 0. And last SentiWordNet has just sentiment values.

"Algorithm for loading the wordlist is as follows:

1. Load SMART word list into a HashMap.
    a. Entry example, key = 'impossible'; value= '-3, 0, 0, 0, 3, 3, 0, 0, 0'.
    b. Values are 1= sentiment score, 2=joy, 3=trust, 4=fear, 5=surprise, 6=sadness, 7=disgust, 8=disgust and 9=anticipation.
    c. Here -3 is the sentiment weight. Since emotion present in this example are 'sadness and surprise' the respective values contain the number '3'.
2. Load NRC word list into HashMap.
    a. Entry example, key = 'protest'; value= '-1, 0, 0, 0, 0, 0, 1, 0, 1'.
    b. Same values as SMART word list.
3. Load SentiWordNet into HashMap.
    a. Entry example, key = 'protestNNS'; value= '-0.63'.
    b. Here the key is the word and its POS tag and value is sentiment weight on a -1 to 1 scale" (Desai, 2014) .

5.6.1.2 Emotion Labelling

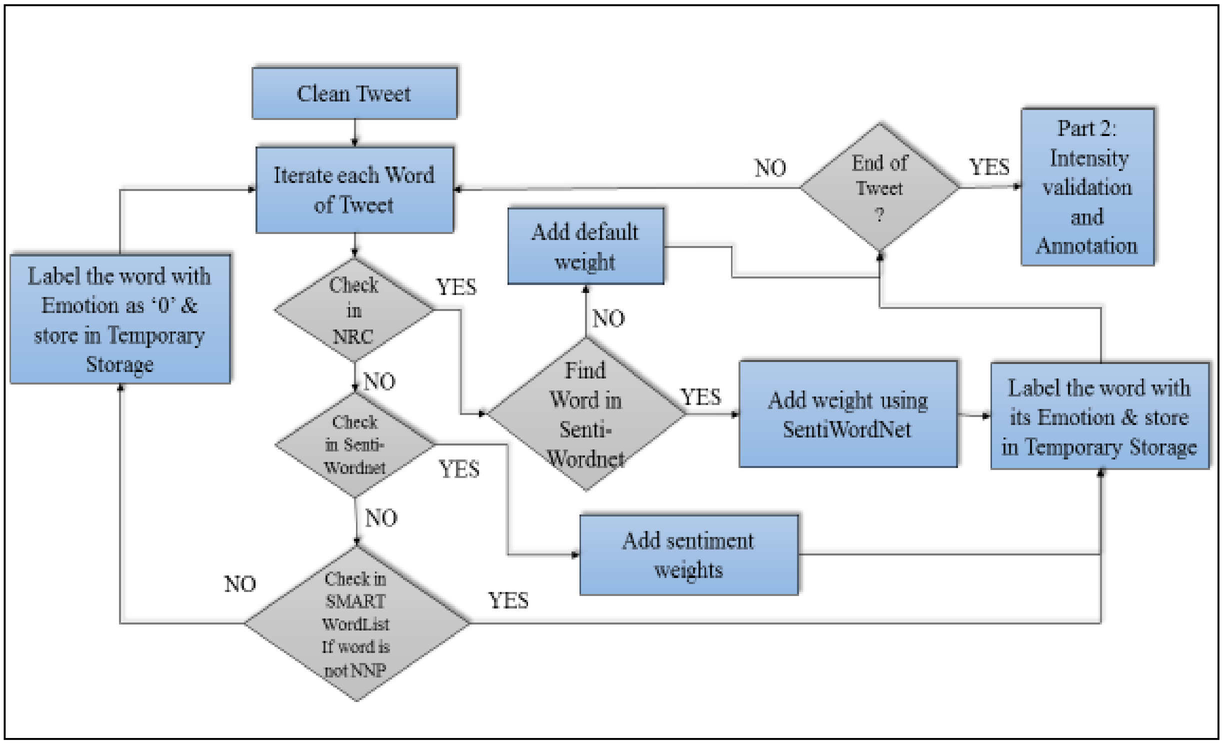


Figure 10: Emotion Labelling

(Desai, 2014)

Let us take an example mentioned in SMART SEA project, Consider following tweet after preprocessing:

"Protest in #Ukraine is not a hopeless situation for #Russian government"

First, hopeless word is found in NRC wordlist with sentiment -1, Surprise and Disgust as 1 and word is found in SentiWordNet with weight as -3. So we update as follows:

Table 1: Entry of the word hopeless in NRC word list (Desai, 2014):

Word	Sentiment	Joy	Trust	Fear	Surprise	Sadness	Disgust	Anger	Anticipation
hopeless	-3	0	0	0	3	0	3	0	0

Then word protest was not found in NRC or SentiWordNet so we checked in SMART:

Table 2: Entry of the word protest in SMART word list (Desai, 2014):

Word	Sentiment	Joy	Trust	Fear	Surprise	Sadness	Disgust	Anger	Anticipation
protest	-2	0	0	0	0	0	2	0	2

Now Initial tweet in internal storage: Each word has its POS tagging

Table 3: Initial Tweet in Internal Storage (Desai, 2014):

Word	Sentiment	Joy	Trust	Fear	Surprise	Sadness	Disgust	Anger	Anticipation	POS
protest	0	0	0	0	0	0	0	0	0	NNS
In	0	0	0	0	0	0	0	0	0	IN
ukraine	0	0	0	0	0	0	0	0	0	NN
Is	0	0	0	0	0	0	0	0	0	VBP
Not	0	0	0	0	0	0	0	0	0	RB
A	0	0	0	0	0	0	0	0	0	DT
Hopeless	0	0	0	0	0	0	0	0	0	JJ
Situation	0	0	0	0	0	0	0	0	0	NN
For	0	0	0	0	0	0	0	0	0	IN
russian	0	0	0	0	0	0	0	0	0	NN
government	0	0	0	0	0	0	0	0	0	NNS

4.6.1.3 Valence Shifter and Intensifiers

In this words are checked against valence shifter and Intensifier list. In our example, we find valence shifter as NOT, so check for next senti word and flip the sign of its sentiment and swap values in the emotions with its counterparts. If it was an intensifier, then increase the intensity of the next immediate emotion word by one.

In our example, we find NOT followed by hopeless word so we change its values and calculate Total Score as follows:

Table 4: Valence Shifter and Intensifier and Total (Desai, 2014):

Word	Sentiment	Joy	Trust	Fear	Surprise	Sadness	Disgust	Anger	Anticipation	POS
protest	-2	0	0	0	0	0	2	0	2	NNS
In	0	0	0	0	0	0	0	0	0	IN
ukraine	0	0	0	0	0	0	0	0	0	NN
Is	0	0	0	0	0	0	0	0	0	VBP
not	0	0	0	0	0	0	0	0	0	RB
A	0	0	0	0	0	0	0	0	0	DT
hopeless	3	0	3	0	0	0	0	0	3	JJ
situation	0	0	0	0	0	0	0	0	0	NN
For	0	0	0	0	0	0	0	0	0	IN
russian	0	0	0	0	0	0	0	0	0	NN
government	0	0	0	0	0	0	0	0	0	NNS
Total	1	0	3	0	0	0	2	0	5	

Out of all these attributes, we were just interested for Sentiment Score if it is positive or negative and the Sadness feature if it is present in the statement or not. Rest all attributes, we did not take into consideration (Desai, 2014)

4.7 Check Self Related Tweets

Next step in our architecture is to check self-related tweets. Dr. Walter Weintraub, Professor of psychiatry at the University of Maryland School of Medicine, has studied about people's everyday used words. According to his research, "first-person singular pronouns (e.g., I, me, my) were reliably linked to people's levels of depression" mentioned in the Tausczik' s paper (Tausczik & Pennebaker, 2010). Also, there was a news article in the Daily Mail newspaper by Emma Innes, "Scientists at the University of Kassel, Germany, found that the people who use first-person singular pronouns the most are more likely to be depressed than those who tend to use plural pronouns, such as 'we'.

People who say 'me', 'myself' and 'I' frequently are more likely to suffer with depression and anxiety” (Innes, 2013).

Since our major interest was to study mental disorders, we decided to consider this factor. Linguistic Inquiry and Word Count (LIWC) is a text analysis program that counts words in psychologically meaningful categories. So, LIWC 2007 wordlist has more than 200 different categories. We used words related to self, or first person pronouns. We considered following words in our list: self, I, am, myself, me, id, i'd, i'll, im, i'm, ive, i've, mine, own, myselves.

We checked every single tweet against this *Myself Wordlist* to verify if the tweet has any self-related words. If it matches with the word list, we label that tweet as “Self”, else we label as “nSelf”. So, to the next level of architecture, we consider if the tweet is self or not and pass it thorough decision tree.

A below mentioned figure shows that, how we get self and nself tweets, Mental Disorders (MD) Score, Sentiment Score and Sadness Score:

protweet	category	Score	SentiScore	Sadness	label
when i'm depressed i over think and when i over think i feel like i don't have control whic...	Depression	9	-1	3	self
i deserve all the pain i have i'm a fucking horrible person i hate myself so much i hope i ...	Depression	8	-5	11	self
i don't care i don't care i don't care i don't care i don't care i don't care i do care and...	Depression	8	-4	4	self

protweet	category	Score	SentiScore	Sadness	label
ion think adrian know he bipolar ud83d ude29	Depression	2	0	0	nself
crisis hotline for veterans winner lets talk about suicideoscars	Depression	1	-4	5	nself
based on how the show is going we probably should start talking about suicide	Depression	1	-3	5	nself

Figure 11: Check Self Related Tweets

4.8 Classification

We have classified tweets into 4 different classes. Classification is an important step in our research. Classification classes are as follows:

1) Most,
2) Moderate,
3) Least and
4) NA (Not Applicable).

Here we classify as most/moderately or least potentially suffering from or having symptoms/signs of any of the mental disorders which we have considered.

The people who are not talking about themselves and are talking in general about mental disorders for creating awareness or talking about their relatives/friends etc., we label these tweets as Not Applicable (NA).

Here is the snapshot of classified classes:

protweet	category	Score	SentiScore	Sadness	label	class
but it's because at a point in my life i suffered from depression	Depression	2	-2	2	self	least
pretty sure i'm bipolar	Depression	1	1	0	self	least
march is gonna make or break my mental health	Depression	2	1	0	self	least

protweet	category	Score	SentiScore	Sadness	label	class
my mood rn is awful i feel so extra bipolar ud83d udc86	Depression	4	0	3	self	moderate
my anxiety depression is destroying me but what does it matter anymore	Depression	3	-1	0	self	moderate
if u use the term stressed depressed , arghhhhh i am sick of all this	Depression	4	-3	6	self	moderate

protweet	category	Score	SentiScore	Sadness	label	class
when i'm depressed i over think and when i over think i feel like i don't have control whic...	Depression	9	-1	3	self	most
i deserve all the pain i have i'm a fucking horrible person i hate myself so much i hope i ...	Depression	8	-5	11	self	most
i don't care i don't care i don't care i don't care i don't care i don't care i do care and...	Depression	8	-4	4	self	most

protweet	category	Score	SentiScore	Sadness	label	class
ion think adrian know he bipolar ud83d ude29	Depression	2	0	0	nself	NA
crisis hotline for veterans winner lets talk about suicideoscars	Depression	1	-4	5	nself	NA
based on how the show is going we probably should start talking about suicide	Depression	1	-3	5	nself	NA

Figure 12: Classification of Tweets

4.8.1 Labelling Rules

For the classification purpose, we have designed our own rules as described in the following figure:

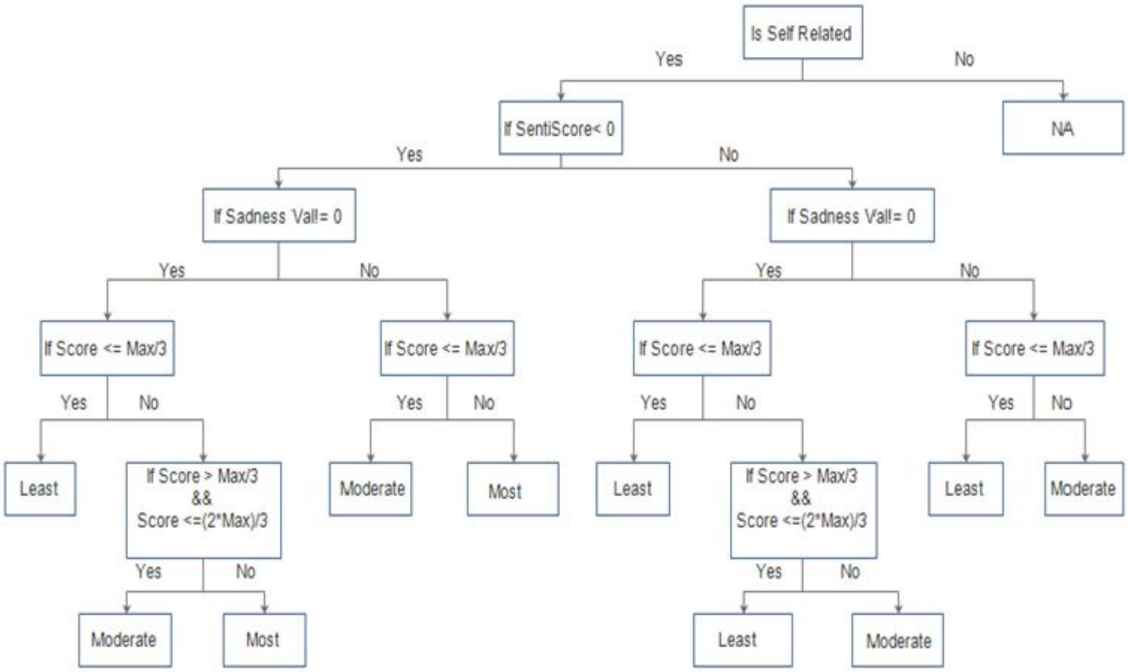


Figure 13: Labelling Rules

It has four different levels of filtration criteria: First it checks, if the tweet is self-referenced or not. If it is self-referenced, then the sentiment score is checked. If SentiScore is less than zero, then sadness value is checked: if it is some positive value, then we check *mental disorders dictionary* score. As discussed above, after calculating outlier, we have maximum score, which is divided into three equal ranges. Followed by this, we check if the score falls into which range. If it is in the first range, then it is labeled as *least*, else *moderate*, else *most*.

But, even if SentiScore is positive, there might be the case, in which it will have high sadness score, so we check all the conditions again. There are also cases, where

SentiScore is positive and sadness score is zero, but there could be a possibility of that dictionary score is very high, so we did not want to miss such conditions.

4.9 Follow Users

After the classification step, almost 1000 users are classified as '*most*' (depressed). Our goal was to follow them for a certain period.

According to psychologists, depressed people tend to make more use of self-referenced words, they always have negativity in their conversation, and they feel sad, lonely all the time. They interact less with the crowd. Other mental disorders such as schizophrenia or anxiety do not fall into these categories of signs or symptoms. So, we did not follow people from these groups.

Twitter streaming API has certain constraints on the amount of data you can fetch. Because of this difficulty, we could not follow all 1000 people on Twitter.
So we decided to follow random 200 people from the dataset for 1.5-3 months duration on Twitter to watch their activities.

4.10 After Follow

We analyzed these 200 users' tweets after following on Twitter. For the analysis purpose, we have used word lists created by psychologists Dr. James W. Pennebaker. The dictionary is named as Linguistic Inquiry and Word Count LIWC 2007 (Pennebaker Conglomerates, 2015). The dictionary has 464 different dimensions, which has millions of words. Dimensions are *function words, affect words, social words, swear words* etc. We were interested in analyzing *function words*, which have self-referenced words. Affect words are also analyzed which has positive and negative emotions. We then matched a tweet against our four different wordlists named *self, negative, positive* and *social*. Finally we get individual scores out of 100.

protweet	category	Score	SentiScore	Sadness	Myself	NegEmotions	PosEmotions	Social	label
i am such a big waste of space i'm so sorry	Depression	0	-6	4	66.666667	33.333333	0.000000	0.000000	self
sorry loses it's impact sincerity when you are constantly saying it for something y…	Depression	0	4	3	0.000000	33.333333	0.000000	66.666667	nself
i want someone to know me well enough to know the answer before even asking the…	Depression	0	-1	0	33.333333	0.000000	16.666667	50.000000	self
knowing that people care about me should make me feel happy and loved but all it d…	Depression	5	-2	0	30.000000	40.000000	20.000000	10.000000	self
how did i allow food to become such a horrible thing to deal with	Depression	2	-4	1	25.000000	50.000000	0.000000	25.000000	self
ironically whenever i'm full i feel gross like i did something wrong or should feel guilty	Depression	4	-7	2	40.000000	60.000000	0.000000	0.000000	self
every time i eat something that isn't perfectly healthy for me my mind just says yo…	Depression	2	0	0	50.000000	50.000000	0.000000	0.000000	self
crying cutting pill taking i can't do this anymore	Depression	3	-6	6	33.333333	66.666667	0.000000	0.000000	self
i don't want to wait for the down set date cause i would rather end it all tonight	Depression	2	1	0	50.000000	50.000000	0.000000	0.000000	self
i'm done please be the end	Depression	1	0	0	0.000000	50.000000	50.000000	0.000000	self
the thing is people know fine what sets me off they know what i can't cope with yet …	Depression	2	0	0	37.500000	12.500000	12.500000	37.500000	self
you dont understand nno one does	Depression	0	0	0	0.000000	0.000000	0.000000	100.000…	nself

Figure 14: After Follow

Then for the evaluation purposes, we calculated average scores for all of them as shown in the Figure 14.

Result Grid | Filter Rows: | Export: | Wrap Cell Content:

AVG(Myself)	AVG(Sadness)	AVG(NegEmotions)	AVG(PosEmotions)	AVG(SentiScore)	AVG(Social)
43.6111110833	2.9167	18.3961640000	3.0092592500	-3.0000	26.6501322500

Figure 15: After Follow Users' Average Scores

4.11 Seasonal Affective Disorders

According to WebMD, Seasonal Affective Disorder (SAD) is a type of depression, which occurs as the season changes. "Seasonal depression is a mood disorder that happens every year at the same time. A rare form of seasonal depression, known as "summer depression," begins in late spring or early summer and ends in fall. In general, though, seasonal affective disorder starts in fall or winter and ends in spring or early summer" (WebMD, 2015b). Following are the symptoms of SAD during the winter season, according to (WebMD, 2015b):

- Less energy
- Trouble concentrating
- Fatigue
- Greater appetite
- Increased desire to be alone
- Greater need for sleep
- Weight gain

Symptoms of SAD during summer:

- Less appetite
- Trouble sleeping
- Weight loss

Seasonal affective disorder is also known as winter depression, winter blues or summer depression, summertime sadness etc.

4.11.1 Causes of SAD

There are two major causes of SAD: lack of sunlight and deficiency of Vitamin D.

A researcher from UGA has also found a strong connection between seasonal affective disorder and lack of sunlight.

"Seasonal affective disorder is believed to affect up to 10 percent of the population, depending upon geographical location, and is a type of depression related to changes in season," said Stewart, an Associate Professor in the Department of Counseling and Human Development Services. Evidence exists that low levels of dopamine and serotonin are linked to depression, therefore it is logical that there may be a relationship between low levels of vitamin D and depressive symptoms," said Kimlin, a Cancer Council Queensland Professor of Cancer Prevention Research" (Stewart, 2014). Because of this, more people tend to get depressed in winter season since there is less sunlight and hence deficiency of vitamin D.

According to Dr. Shock, "the highest seasonal incidence occurred in winter and decreased as the season changed from winter to autumn, the monthly cases reached it's high in March and it is lowest in September" (Li et al., 2011).

In our research, goal was to observe how people react to seasonal depression in social media and the pattern as the season changes. We extracted tweets from Twitter using certain keywords related to seasonal affective depression. The keywords are *winter depression, winter schizophrenia, winter blues, seasonal affective disorder, summer depression, summertime blues, summertime sadness, summer onset SAD, depression in fall season* etc.

As discussed in the architecture above, we classified tweets as relevant or irrelevant. Following is the screenshot of some tweets related to Seasonal Affective Disorder:

user	dateTime	protweet	category	class
UbayZulfikar	Tue Jun 02 01:26:48 +0000 2015	seasonal affective disorder not as common as thought	SAD	NA
Pope_BaneXXIII	Tue Jun 02 02:31:43 +0000 2015	i think i might have sad seasonal affective disorder my mood is so low in this cold weather	SAD	moderate
MitchsRightLeg	Tue Jun 02 02:47:05 +0000 2015	i swear i should see if i have the seasonal affective disorder cuz i always have no motivation and everything gets ba...	SAD	most
kushnrainbows	Tue Jun 02 03:34:56 +0000 2015	i feel like i have seasonal depression lol i be so turned down in the winter	SAD	most
loomishamilton	Tue Jun 02 03:46:29 +0000 2015	i'm struggling with seasonal affective disorder and the season is mariners baseball	SAD	moderate

Figure 16: Tweets about Seasonal Affective Disorder

CHAPTER 5

RESULTS AND EVALUATIONS

5.1 Our Results in Twitter and Real-life Mental Disorders

The goal was to analyze and identify people with symptoms of mental disorders from social media like Twitter. We analyzed five disorders, including depression, schizophrenia, anxiety disorders, drug or alcohol abuse and seasonal affective disorders. The results for each of them are as follows:

1) Depression:

- Total Unique Users (Relevant + Irrelevant) = 2,149,308
- Relevant Unique Users = 722,916
- Most = 904
- Moderate = 89,075
- Least = 632,937
- Potential Users with Depression = 33.63%

2) Schizophrenia:

- Total Unique Users (Relevant + Irrelevant) = 21,896
- Relevant Unique Users = 2,335
- Most = 5
- Moderate = 299
- Least = 2,032
- Potential Users with Schizophrenia = 9%

3) Anxiety Disorders:

- Total Unique Users (Relevant + Irrelevant) = 638,009
- Relevant Unique Users = 322,855
- Most = 12,020
- Moderate = 39,645
- Least = 271,190
- Potential Users with Anxiety Disorders = 48%

4) Drug or Alcohol Abuse:

- Total Unique Users (Relevant + Irrelevant) = 45,203
- Relevant Unique Users = 10,966
- Most = 109
- Moderate = 4,118
- Least = 6,739
- Potential Users with Drug or Alcohol Abuse = 24.25%

5) Seasonal Affective Disorder:

- Total Unique Users (Relevant + Irrelevant) = 36,029
- Relevant Unique Users = 88,71
- Potential Users with Seasonal Affective Disorder = 24.62%

Results of all Mental Disorders:

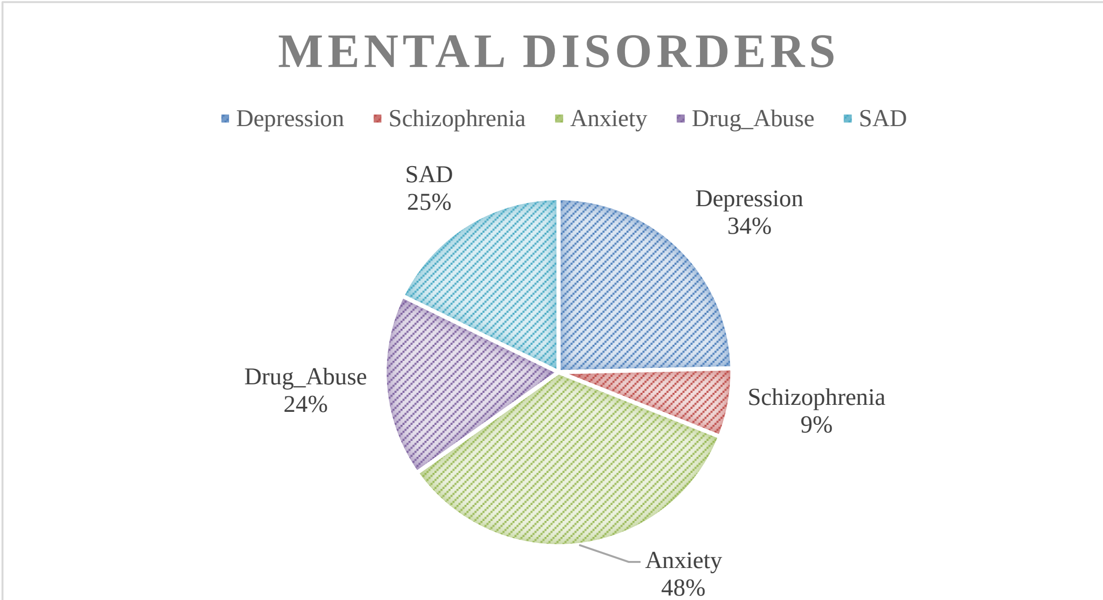


Figure 17: Mental Disorders

Results by classification:

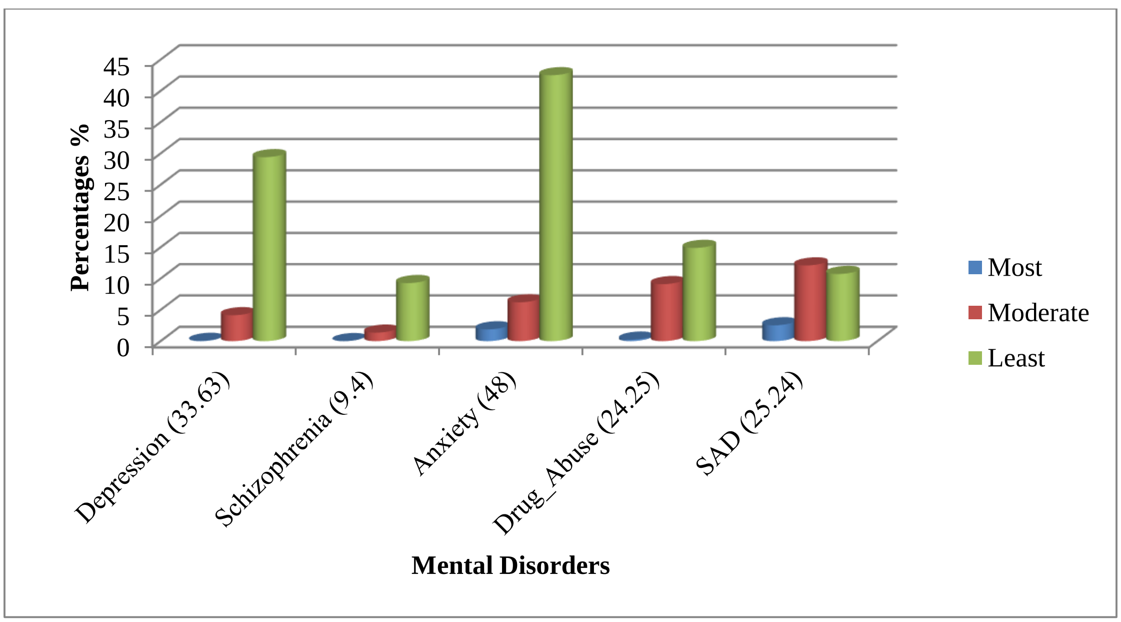


Figure 18: Mental Disorders by Classification

The above statistics represents only Twitter users all the over the world.

According to (Vikram Patel, 2014) in New England of Medicine Journal, “ At least 10% of the world's population are affected by one of a wide range of mental disorders; as many as 700 million people had a mental disorder in 2010. The 2010 Global Burden of Disease Study showed that mental disorders account for 7.4% of the world's burden of health conditions” (Vikram Patel, 2014). The contribution of different mental disorders to this burden is shown below which is close to results in our study:

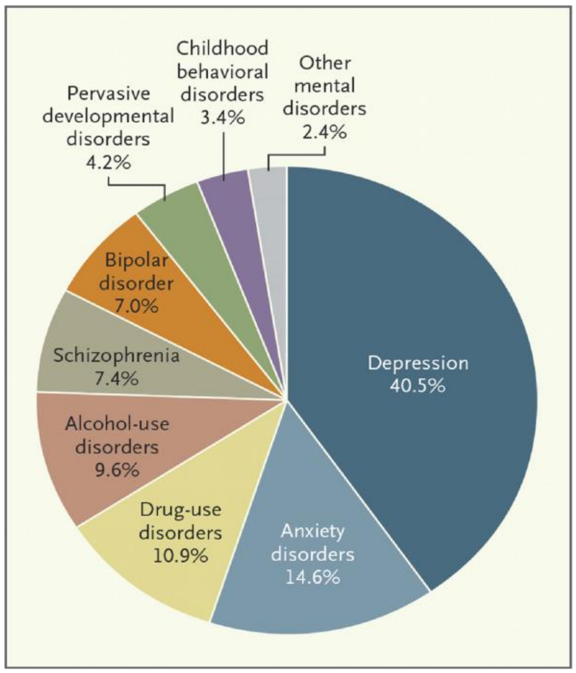


Figure 19: Contribution of Different Mental Disorders

(Vikram Patel, 2014)

5.1.1 Results of Seasonal Affective Disorders

As described in Section 5.11, more people tend to suffer from seasonal affective disorder in the winter season than summer, because of less sunlight, which leads to deficiency of vitamin D.

Our purpose was to analyze these results from social media. We wanted to analyze how social media are closely associated with real life.

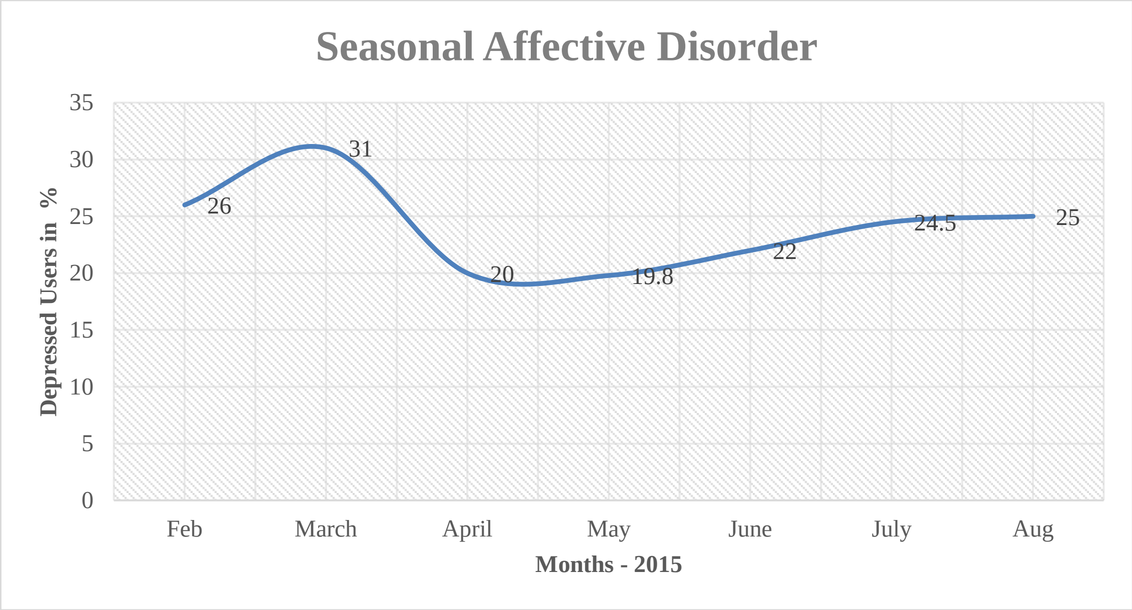


Figure 20: Seasonal Affective Disorder Pattern

The above figure demonstrates SAD pattern from February to Sept in 2015. It is observed that % count is higher in Feb, and March, which being considered in winter season. Then it decreases suddenly and increases slightly when the season changes.

5.2 Evaluation Procedure

In this chapter, we discuss the evaluation procedure and accuracy of the system.

Finding accuracy of the system was a major challenge because of the necessity of human judgment. We asked a small group of people to evaluate our results. Since each human being has a different perspective, it is highly unreliable to rely on just one person's opinion. So, for the evaluation process three different people are targeted and finally majority opinion is considered which is checked against our system to find the accuracy.

In our approach, testing is performed at two different levels in the database. One at the *classification level* and second at the *after follow* step. We looked at several ways for the evaluation purpose, and then decided to evaluate overall 800 random tweets and 100 (follow) users from the database.

5.2.1 Testing 1

We asked examiners to provide their input on the accuracy of our system. Each examiner is provided with an excel sheet, which had 200 random tweets from the dataset. Each examiner's identity is kept anonymous.

Examiners were provided with an excel sheet of the following format:

User	Tweet	Relevant/Irrelevant
1	im n depression	R
2	volunteer muhammed for the next suicide bombing n	I
3	np insomnia ryeowook	I
4	beauty tips 594 bipolar derma care radio frequency rf collagen anti aging stretch mark re u2026	I
5	this broke my heart n nalwaysinourheartszaynmalik	R

Figure 21: Screenshot of Testing 1

The column under "User" is the actual user from Twitter whose identity is kept anonymous. "Tweet" column contain tweets, which we are analyzing and "Relevant/Irrelevant" contains the answer (from an examiner), if it is relevant or irrelevant to the given domain.

<u>Definition of Relevance:</u>

An examiner had to check, if a user had signs or symptoms related to mental disorders and if a user is talking about himself or herself.

Let’s take an example: if an user’s tweet has self-related words like I, am, me, myself etc., then a person is talking with respect to himself and he has symptoms/signs related to any of these disorders: Depression, Schizophrenia, Anxiety, Drug Abuse and Seasonal Disorders.

Two sample tweets are presented below and they are usually considered relevant in Testing 1:

- I hate myself for not being good enough for you
- I always get so depressed when i get down to my last box of totino's ud83d ude33

<u>Definition of Irrelevance:</u>

We are interested in checking, if a user is suffering from mental disorders; so if a tweet is talking about a third person, examiner should mark it as irrelevant. For example, consider the following irrelevant examples:

- your guide to recovery depression bipolar mindfulness
- my mom is suffering thorough depression.

We provided Excel sheet to three different evaluators as Examiner 1, Examiner 2 and Examiner 3 with the same set of 200 tweets. And, then we considered, majority opinion out of three examiners.

5.2.2 Testing 2

Similar to Testing 1, we asked examiners to provide their opinions on the accuracy of our system. We provided users with an Excel sheet, which had tweets of 25 users, which are followed on Twitter for 2-3 months.

This file had tweets related to only ‘depression’ criteria and not related to any other mental disorders. The examiner were provided with a excel sheet in the following format:

User	All Tweets	Myself (Low/High)	Neg/Pos
1	i am drowning in life's ocean		
	i'm drowning in my own thoughts		
	meet me in outer space		
	thanks for not caring		
	you can u2019t do this you can u2019t build my hopes up and then leave me alone you can u2019t stop that u2019s not cool		
	i've changed oh pain seems to do that to people i suppose		
	thank you all ud83d udd2e		
	its just that i dont really believe in happy endings me		
	why do i have friends i'm so fat ugly and worthless		
	i wish i didn't suck at keep conversation going and keeping contact and stuff		
	can you fucking not		
	anxiety feels like when you miss a step on the stair case over and over and over		
	when you have been sad for so long that when something bad happens you don't cry you just sit there and feel numb		
	hate getting flashbacks from things you don't want to remember it feels like your heart suddenly drops and anxiety st u2026	High	Neg

Figure 22: Screenshot of Testing 2

The column under ‘User’ is the actual user from Twitter whose identity is kept anonymous. ‘All Tweets’ column has all the tweets of this user over 2-3 months. Examiner had to read all the tweets of the same user and had to mark the corresponding column of Myself as Low/High and Negative/positive.

- If a User is talking about himself in the text again and again, i.e. if a person is self-referencing (More use of I, me, myself words) then, it was marked as High else Low.
- Examiner checked if tweets had more negativity than positivity then, marked it as Neg otherwise Pos.

The purpose behind Testing 2 was to check if a particular user is having signs of depression by identifying whether he/she is self-referencing frequently and uses more of negative words than positive in his/her tweets.

Similar to Testing 1, we provided three different examiners with same 25 Users' tweets and asked for the evaluation. And then we considered the majority opinion, and tested against our system.

5.2.3 Results after Follow Users

We followed almost 200 users on Twitter for 1.5-3 months duration to check their activities in terms of different parameters. Following screenshot demonstrates results after following each user:

User	count(tweet)	Myself	Sadness	Neg	Pos	SentiScore	Social
inlovewxthbones	70	28.78628116	2.0143	27.58799929	7.683019371	-1.2429	24.514129
DemiiiPritchard	19	30.55555558	1.9474	26.46825389	11.50584795	-0.1053	31.470343
philosoraptress	346	29.82248723	0.6821	19.61617862	15.37029684	0.5318	17.560979
AnaL_xDepressed	52	35.6214779	1.5192	33.91043246	6.497781077	-1.2692	20.124155
AnxietyIsYou	26	29.91946081	3.3846	30.13231427	10.491453	-1.3846	17.91831
BebeRexhaf	40	30.4876928	3.1	39.34423908	9.614774075	-2.55	18.053294
Just_KillMeNow_	908	28.95577684	0.8546	24.13113318	9.764660508	0.0639	20.077945
mez90584759	22	28.33333332	3.0455	34.88275614	3.459595955	-2.9545	24.233405
suicidalmisfits	48	28.95833333	1.4583	38.53535352	7.118055563	0.7292	12.888258

Figure 23: After Follow results per User

5.2.4 The agreement between our system and examiners

We have evaluated 800 random tweets and 100 users from the database as discussed above in the testing section. Each examiner evaluated 200 tweets and 25 users and same set of tweets are given to three different evaluators and majority is considered.

Table 5: Testing 1

Tweet	Evaluator 1	Evaluator 2	Evaluator 3	Majority Opinion	Our System	Accuracy
Hate myself	Relevant	Irrelevant	Relevant	Relevant	Relevant	Correct

So out of 800 tweets, 676 tweets are marked relevant by human examiners. Hence the agreement is 84.59 %.

For Testing 2, if *Myself Score* less than 20% in our results, it is considered as a low score. Similarly, if *Neg Score* is greater than *Pos Score,* then *Neg Score* is considered.

Table 6: Testing 2 a: Self Evaluation (Low or High)

User	Tweets	Evaluator1	Evaluator2	Evaluator3	Majority Opinion	Our System	Accuracy
1	--------	Low	High	High	High	High	Correct

At this level, 83 users out of 100 were evaluated correctly. Hence the agreement is 83%.

Table 7: Testing 2 b: Sentiment Evaluation (Pos or Neg)

User	Tweets	Evaluator1	Evaluator2	Evaluator3	Majority Opinion	Our System	Accuracy
1	--------	Pos	Neg	Neg	Neg	Pos	Incorrect

At this level, the agreement between our system and examiner is 79%.

CHAPTER 6

RELATED WORK

6.1 Social Media and Mental Illness

Park, Cha et al. analyzed real time moods of users and tracked how users interact with one another on social media. In this research, random tweets were analyzed from twitter over the two months duration, authors found that people who are suffering from mental illness, their tweets are related to more of negative emotions and anger than positive. They also examined the use of language to perform sentiment analysis. Now a day it has become a trend to share one's private information, be it good or bad on social networking websites. Such clinically depressed people also share their depressed thoughts/feelings, clinical history online. They tend to talk more about themselves, as the use of first person pronoun is more in the text. Tweets were labelled manually based on nine different categories such as sharing, self-promotion, opinions, random thoughts, me, questions to others, presence, maintenance, anecdotes from me and anecdotes by others etc. This was conducted in three steps: "first they surveyed users to identify their self-judged depression level. Then they collected tweets from the same user from twitter and finally compared depression levels of users with their sentiments and language usage in tweets" (Park, Cha, & Cha, 2012).

Finally, sentiment analysis was being performed on the tweets using LIWC sentiment tool. "LIWC is Linguistic Inquiry and Word Count which is a text analysis program that counts word in psychologically meaningful categories" (Pennebaker, Mehl,

& Niederhoffer, 2003). “The LIWC tool contains a dictionary of several thousand words, where each word is scaled across six different criteria: social, adjective, cognitive, perceptual biological processes and relativity. Each type has subtypes which have particular scores assigned in it”. So using this, overall score was calculated to classify tweets. This research had few limitations. LIWC alone wasn’t efficient tool for sentiment analysis as it excludes emoticons, also there were less participants involved in this study (Park et al., 2012).

De Choudhury, Gamon et al.2013 demonstrated an association between 200 different measures to predict depressive disorders ahead of time. They also expanded the scope of identifying mental health factors from social networking websites. The text may indicate feelings of worthlessness, guilt, helplessness, and self-hatred etc. The main contributions of this paper were as follows: “They used a crowdsourcing technique from twitter users who had been diagnosed with clinical Major Depressive Disorders (MDD) using CES-D (Center for Epidemiologic Studies Depression Scale) screening test as a tool to determine depression levels of the crowd workers from AMT. Based on tweet results, they used several measures like user engagement, emotion, egocentric graph, linguistic style, depressive language use and antidepressant usage to measure users’ behavior. Followed by this, they compared the behaviors of the depressed users and the standard users, which showed users with depression has lowered social activity, greater negative emotions, high self-attentional focus, increased relational and medicinal concerns and heightened expression of religious thoughts. For emotion measure, along with LIWC, they used ANEW lexicon (Bradley & Lang, 1999) for finding activation and dominance which refers to the degree of physical intensity in an emotion and the degree of control in an emotion. Finally, they used a supervised learning technique to build MDD classifier which predicts if the user is susceptible to depression or not. The results were similar to Park et. Al., (2012) who scored positive for depression. The accuracy of this system was 70% and precision 0.74" (De Choudhury, Gamon, Counts, & Horvitz, 2013).

Detecting depressed users from social media was also supported by Wang, Zhang (2013). The study demonstrates data from social media and how it is important to psychology as well as sociology. It detects depressed users in Sina Micro blog which is similar to Twitter, a social networing website and it is very popular in China. It has contributed in four different aspects: For the depression analysis, data mining technique is used. Depression intensity is being calculated using Sentiment Analysis technique and Chinese micro-blog is used. For this, they proposed the list of vocabulary related to depression, which was developed from HowNet (Zhang, Zeng, Li, Wang, & Zuo, 2009) and from Chinese syntax rules, sentence pattern and rules for calculations were derived in order to find depression inclination.

They proposed depression detection model based on above two criteria and 10 characteristics of depressed users from psychological study. This proposed model has three major steps as follows: As microblog allows 140 characters in a sentence, using punctuation as a symbol, sentence is segmented along with word segmentation. Using the polarity calculation algorithm, polarity of each word is being calculated followed by the polarity of the entire sentence. Model also considered the psychological aspects of a person such as use of first person singular or plural pronouns, use of emoticons, interaction with other users, and behavior of the user on social media. After all this, users were classified as depressed or normal users using different classification techniques. Waikato Environment for Knowledge Analysis (Weka) tool was used for this purpose (Han & Kamber, 2006). In order to make it more reliable and to verify the model, three different classifiers such as Bayes, Trees and Rules were used (Han & Kamber, 2006). The proposed model with all classifiers has around 80% of precision. But this had few limitations as, first it was subjected to only Chinese microblog and so Chinese language. Although the vocabulary was all based on Chinese language, the model can be applied to different languages and second the dataset was small so it is difficult to analyze how reliable is this model for large dataset. In spite of all this, proposed framework helped psychologist to detect potentially depressed users, improving public health (Wang et al., 2013).

According to Reavley and Pilkington 2014, “social networks provide sensible information for capturing depressive moods of users” (Reavley & Pilkington, 2014). The paper states that, this research might help scientist to promote mental health and create awareness amongst common people. The study provides evidences of how twitter users share information about depression or schizophrenia on social media and what type of information they share. Twitter data was being collected over the period of 7 days based on hashtags namely #depression and #schizophrenia. Followed by this content analysis was being performed using Nvivo 10 which is used to analyze unstructured data type. “The second author coded the tweets based on the extent to which they indicated a particular attitude towards depression or schizophrenia. Tweets were categorized based on their content and user information. The following content themes emerged: (1) personal experience of mental illness, (2) awareness promotion, (3) research findings, (4) resources for consumers (5) advertising, (6) news media, (7) personal opinion or dyadic interaction" (Reavley & Pilkington, 2014). Another criteria was to identify type of users. They found users who were tweeting about depression were either consumers, organizations to create awareness or mental health advocates. And majority users, who tweeted about schizophrenia were individuals, organizations, health professionals, mental health advocates or consumers. They also researched about the content type of the tweets, attitude towards depression or schizophrenia like if the opinion is neutral, supportive or against etc. Although the study supported analysis of tweets towards mental illness, it had a few limitations. The research could not identify how many tweets were exactly referring to depression and anxiety. Dataset was proportionally small, as only tweets over 7 days were collected and, other than depression and schizophrenia hashtags, slang terms could have been missed in the dataset (Reavley & Pilkington, 2014).

"The results from this paper could be compared with Martinez-Perez et al. (2014), who analyzed the purposes and functions of Facebook and Twitter groups for different mental illnesses, including depression. They classified groups according to whether they were support groups, self-help groups, advocacy and awareness groups and fundraising groups. They concluded that self-help groups were the most common category (64%), followed by support groups (15%), and advocacy and awareness groups (10%)"(Martínez-Pérez, de la Torre-Díez, Bargiela-Flórez, López-Coronado, & Rodrigues, 2014).

Schwartz et al. (2014) used Facebook as a social networking media to predict one's level of depression displayed socially using their language. Regression model was built by them to characterize depression. This research was entirely based on how users express their depression through language. They analyzed use of language in order to predict depression. Two years dataset from Facebook was being considered followed by user's degree of depression was calculated. LIWC (Pennebaker et al., 2003) categories were used to find out lexicon. Finally the regression model was built by dividing a dataset as training and testing and sentiment analysis was performed. They also evaluated seasonal pattern while evaluating degree of depression. According to the author, in the future, it is feasible to find degree of depression and changes in depression levels weekly or on a monthly basis (Schwartz et al., 2014).

Banitaan and Daimi (2014) predicted the possible depression cases in future using data mining concept. Data mining is widely used in almost all types of industries to find the association, relation or pattern between different attributes in a dataset. For this research, authors used synthetic data and WEKA a machine learning tool was used for prediction of the depression cases. The method consists of following stages:

Attribute selection, creating models, testing followed by results and analysis.

Fifty different attributes were selected in order to construct a prediction model with corresponding values as none (0), Mild (1), Medium (2) and Serious (3). A well-known decision tree algorithm was used along with machine learning tool WEKA. In this, they applied different rules on the above mentioned attributes and concluded as Yes or No for depression cases. The limitation of this paper was, they used synthetic data which were generated by using JAVA program. So with the actual dataset, it is hard to predict how this model would work. Although the accuracy turned out to be reasonable as 83.25% (Banitaan & Daimi, 2014).

Moreno, Kelleher, and Pumper (2013) evaluated depression symptoms using social media website by developing depression codebook. This codebook can be used and expanded in the future for different disorder cases such as anxiety. They also investigated suicide protocol in this paper (Moreno et al., 2013).

De Choudhury, Counts, and Horvitz (2013) also used social media as a measurement tool of depression in a population. They used crowdsourcing technique to collect data and developed SVM classifier to predict depressive tweets with the accuracy of 73% and along with this geographical analysis of tweets were performed (De Choudhury, Counts, et al., 2013).

Harman (2014) analyzed mental health in his research paper named "Quantifying Mental Health Signals in Twitter". Using natural language processing, they studied post-traumatic stress disorder (PTSD), depression, bipolar disorder, and seasonal affective disorder (SAD) (Harman, 2014).

Preotiuc-Pietro et al. (2015) demonstrated how the personality, age and gender contributes to mental illness on Twitter. They targeted two disorders, namely PTSD and depression along with their symptoms and effects from user's tweets. So they used demographics features to analyze the language of depression using LIWC and binary logistic regression classifiers (Pedregosa et al., 2011) for better prediction results. (Preotiuc-Pietro et al., 2015).

6.2 Summary of Related Work

Table 8: Summary of Related Work**:**

Author	Data	Technique/ Method	Classes for classification	Accuracy
(Park et al., 2012)	Twitter (2 months)	Text analysis (LIWC)	Depressed feelings, delivery, sharing thoughts, others etc.	N/A
(De Choudhury, Gamon, et al., 2013)	Twitter	LIWC, ANEW, Supervised learning technique (SVM).	Depressed, Normal Tweets	70%
(Wang et al., 2013)	Sina Chinese Micro blog (15 days)	Bag of Words, Sentiment analysis-Machine learning (WEKA- Bayes, Trees and Rules classifiers)	Depressed, Normal Tweets	Precision 80%
(Reavley & Pilkington, 2014)	Twitter (7 days)	Sentiment Analysis (Nvivo 10)	Depression & Schizophrenia (Negative, Positive and Neutral)	N/A
(Schwartz et al., 2014).	Facebook (2 years)	Lexica, n-grams, NRC technique based Regression model for classification	Degree of Depression	39%
(Banitaan & Daimi, 2014)	Synthetic Data	Data Mining Technique WEKA- Decision Tree Algorithm	Depressed, Normal Tweets	83.25%
(Moreno et al., 2013)	Facebook & Various Sources	Codebook Development	DSM-IV Criteria's of Depression	N/A
(De Choudhury, Counts, et al., 2013)	Twitter	SVM Classifier	Depressed, Normal Tweets	73%
(Harman, 2014)	Twitter (5 years)	Bag of words, NLP technique	Post-traumatic stress disorder (PTSD), Depression, Bipolar Disorder, and Seasonal Affective Disorder (SAD)	N/A

CHAPTER 7

CONCLUSIONS AND FUTURE WORK

7.1 Conclusion

To conclude, our system has presented a novel approach to analyze different mental disorder cases such as depression, schizophrenia, anxiety disorder, drug or alcohol abuse and seasonal affective disorder. The objective was to offer a platform which is fast, accurate and flexible to identify users and analyze patterns of their writings in terms of language and sentiment.

Our method could identify people diagnosed with or having signs of mental disorders which could lead to depression. The system identified users by analyzing their tweets and classifying them as low, moderate, most or NA users. Also, the proposed method successfully followed users on Twitter to keep a watch on their activities and use of language. It was observed that people diagnosed with depression make greater use of self-referenced words and their language has more negativity.

Results demonstrate that there is a correlation between social media and real life, which can be seen by comparing the results from our system with statistics from the global burden of disease mentioned above. Also, our system could lead to the conclusion that seasonal affective disorder is more prominent in the winter, which closely supports previous psychological findings. This platform will help researchers to identify people with mental disorders at an early stage, to find patterns, and eventually help such victims.

7.2 Future Work

Although the system proposed in this thesis has demonstrated an accurate use of architecture to meet our requirements, it could be further improvised in different ways. The future scope of the system is as follows:

"Many improvements can be made to the system to enhance its performance and scope. For example, adding a new custom bag of words will enable the system to be used in other domains such as 'identifying possible suicide victims on Twitter'" (Desai, 2014).

Improving the detection of self-related tweets could lead to more accurate results from the classification step in the labelling rules.

Exact location of the User is not known from the twitter user profile. So finding geolocation is a challenge. If the location is known, then it could be easier to find people from which area are suffering from these disorders.

Ontology

We have built a domain specific 'Mental Disorder' Ontology, which is in OWL format. It has 1860 Axiom Counts, 51 Class Counts and 12 Object Properties. Ontology has common, slang words or phrases which are frequently used on social media. It depicts different types of mental disorders, symptoms, causes, medications and relationships between them. But, there is a scope for the improvement of this ontology for further analysis.

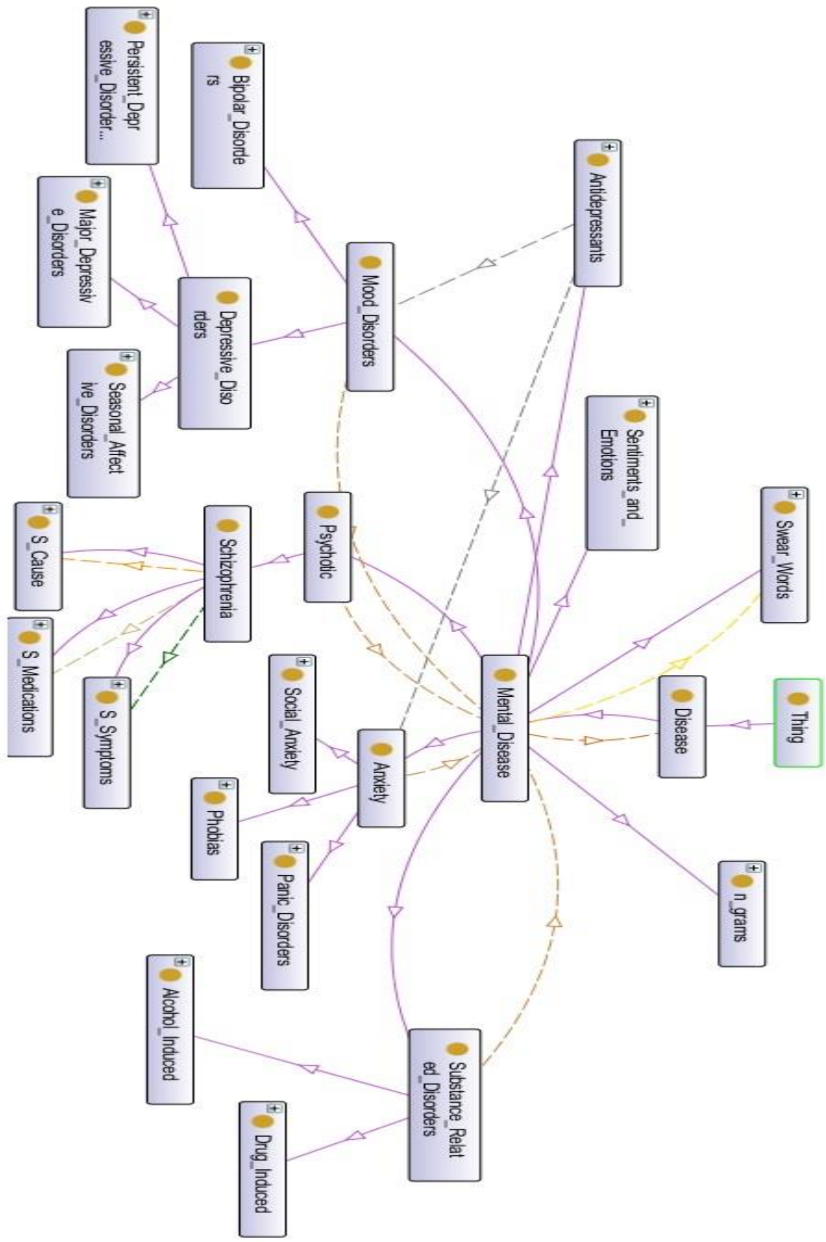


Figure 24: Mental Disorder Ontology

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