Detecting Signs of Depression using Data Analysis and Deep Learning Techniques

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1 Abstract

Around 410 million people worldwide are affected by mental disorders such as dementia, schizophrenia, bipolar disorder, and depression, out of which a major portion of people are affected by depression alone [1]. A patient is considered depressed if any of the symptoms such as ‘depressed mood’, ‘suicidal thoughts’, ‘loss of interest’, ‘feeling worthlessness or hopelessness’ occur daily for at least two weeks [2]. According to the survey held by the World Health Organization (WHO) in 2012, around 1 million people with depression end their lives each year. This makes depression the world’s fourth major disorder [3]. Depression cannot be detected easily, and it has deep and wide-ranging impacts on human life. This independent study contains an investigation of methods for depression detection using publicly available data through social media. Techniques include deep learning techniques such as: CNNs, RNNs, and LSTM. Additionally, an exploration of the visualization tools We Feel, and Sentiment Viz are included.

2 Table of Contents

3 Problem Background and Introduction

Today, a variety of social networking sites like Twitter, Facebook, and Instagram have become a platform for people to express their emotions and opinions happening in their daily lives [4]. Individuals across the world share their ideas, feelings, and opinions by connecting with different people on social networking sites irrespective of demographic and geographic differences [5] [6]. Social media like Twitter and Facebook are used by approximately 65% of the American Adults to share health related information. Such information can be used for investigating various mental disorders [7]. Twitter provides the best platform to apply sentiment analysis or emotion artificial intelligence for depression as Twitter has a fixed limit on the number of characters permitted for a tweet [8]. Sentiment analysis is a text classification task where the machine attempts to derive the sentiment from the text as any other human would have when manually reading the text. It is also known by other names like ‘opinion mining’ [9]. Sentiment analysis helps in evaluating the emotions of people on social networking sites and determines whether the expression is positive, negative or neutral. Thus, the ability to extract sentiment and emotion insights from social data is a practice that is being widely adopted by organizations throughout the world and would also be helpful in the investigation of mental disorders [8].

4 Literature Review

4.1.1 Detecting Signals of Associations Between Dietary Supplement Use and Mental Disorders from Twitter [7]

Studies show that the United States has a high number of mental disorders as compared to other regions. Twenty five percent of adult Americans have been identified with at least one mental disorder [10]. The Paper focuses on the identification of signs of the relationship between dietary supplement usage and mental sicknesses from Twitter [7]. Tweets discussing dietary supplements in the year 2016 to 2017 were taken into consideration for this experiment [7]. The users were divided into two categories, those who take dietary supplements and those who do not. Using a rule-based NLP system based on a previous study to identify supplement use status on the gathered tweets followed by manual verification, it was found that around 257 users have taken dietary supplements out of which 251 users take melatonin [11]. A notable difference in gloomy, anxious and negative emotion between both the groups was observed. These observations were made over time and frequency of mental disorder keyword mentions and sentiments (i.e. positive and negative) and mental health signals (i.e. anger, anxiety, and sad emotions) in the tweets posted before and after supplement use were compared [11]. It was found users who had taken melatonin showed anger, anxiety, and depression more often, which was compatible with the fact that melatonin secretory pattern changes are closely linked to mental diseases [12].

4.1.2 A Framework for Identifying Excessive Sadness in Students through Twitter and Facebook in the Philippines [13]

It has been inspected that depression has a significant influence on students as they have to go through stress and anxiety regularly [13]. The Philippines is known to have the highest depression count in Southeast Asia [13]. The author performed data mining on Twitter and Facebook data and proposed a logistic regression model using natural language processing and sentiment analysis to recognize a user's status [13]. After that, users were clustered into groups to detect major topics of each user and make sense out of every user's extreme sadness, using Latent Dirichlet Allocation (LDA) topic modeling. These clusters were formed based on valid abstract topics from user's social media posts to reveal the cause for their lingering pain accurately [13]. The purpose of this study was to help the users going through depression by familiarizing the users about the topics in a structured manner so that the people could overcome their sadness [13].

4.1.3 Sentiment analysis of social networking sites (SNS) data using machine learning approach for the measurement of depression [8]

This paper used emotion theories, machine learning methods, and natural language processing techniques by extracting and examining sensitive texts posted on various social media sites, to identify the depression level of an individual [8]. The author performed comparisons among Support Vector Machine, Naïve Bayes and Maximum Entropy classifiers for sentence-level sentiment analysis for depression detection [8]. Two types of datasets were utilized for this purpose, Twitter dataset, and 20newsgroups. Various feature extraction methods such as N-gram Features, Part of Speech Tagging (POS), Negation Detection and Sentiment Analyzer were used to detect features from the raw text before applying the machine learning algorithms [8]. It was found that SVM performs better than the other two methods [8]. The accuracy of SVM is 91 %, the accuracy of Maximum Entropy is 80 %, and the accuracy of Naïve Bayes is 83 % [8].

4.1.4 What about Mood Swings? Identifying Depression on Twitter with Temporal Measures of Emotions [14]

This paper proposed a novel methodology by taking data from Twitter posts over some time to detect users going through depression [14]. This method considered eight basic sentiments such as Anger, Disgust, Fear, Happiness, Sadness, Surprise and Shame as features, along with the temporal analysis of these features. The author proposed an EMOTIVE system to detect and measure these fine-grained emotions from a person's tweets, an ontology was applied, produced by [15]. EMOTIVE ontology is nothing but a map of sentiment-related terms and expressions including a set of intensifiers, conjunctions, negators, interjections, and linguistic analysis rules [15]. This ontology provided a deeper semantic description than the usual lexicon and explored sentiments where the intensity of these expressions is used for calculating the strength score. This process was followed by the creation of a Natural Language Processing pipeline that was used to first parse the text and then classify part-of-speech tags. These parsed terms were then compared with the EMOTIVE ontology to match the emotion-related phrases [14]. To determine the strength score, the intensity measures of paired intensifiers for every identified emotion idiom were collected. If the emotion was not present in the post, then a strength score of zero was given to them. The outcomes revealed that basic emotions present significant insights into recognizing twitter users who suffer from depression [14].

4.1.5 We Feel: Mapping Emotion on Twitter [16]

A common problem with large datasets such as the World Health Organization (WHO) is that the statistics are gathered approximately once per year, but social media sites like Twitter can help us in gathering real-time data [16]. The author defined the “We Feel” system, where global and regional changes in emotional expression can be visualized and extracted effortlessly [16]. We Feel used Twitter data for not only analyzing the emotional data throughout the world but also provided real-time data accessible to the research community through a web interface or API. The system examined around 22000 tweets per minute for twelve weeks and produced a high scale, global dataset which can automatically annotate emotions, geographic locations, and gender [16]. This analysis was performed repeatedly to prove possible utilization of the data, where daily and weekly variations in emotional expression were observed using which it was possible to discover significant events that happened in the past [16]. Here the similarities between emotional tweets and signs of anxiety and suicide were observed to showcase that there a possibility of growth in the areas of social media-based measurements that can be used for the improvement of mental well-being [16].

4.1.6 Depression detection using emotion artificial intelligence [2]

The appearance of social media sources has emerged in meaningful user data being accessible for sentiment analysis of text and images. The author used Twitter feeds to conduct sentiment analysis for depression identification by employing natural language processing [2]. Here the posts were classified into two categories, neutral or negative based on a word-list to recognize depression inclinations [2]. Classifiers such as Support Vector Machine and Naive-Bayes were used to predict the signs of depression. The results were evaluated using F1-score, accuracy and confusion matrix [2].

4.1.7 Detecting Depression Using K-Nearest Neighbors (KNN) Classification Technique [17]

The paper examined the probability to use Facebook data and practiced several KNN (k-nearest neighbors) classification techniques for detecting depressive emotions [17]. In the end, the ability to use Facebook data as a source for estimating and identifying major depression amidst users was explicated [17]. Here, four kinds of factors (emotional process, temporal process, linguistic style, and all features) were examined and a model was trained to use each type individually and collectively. It was observed that different types of KNN technique results and ground truth dataset results fluctuate between 60–70% in terms of distinct metrics level [17].

4.1.8 X-A-BiLSTM: A Deep Learning Approach for Depression Detection in Imbalanced Data [18]

Using social media data to discover early depression through deep learning models can save someone's life [18]. But in the real world, the data available is imbalanced which limits the accuracy of these models [18]. To deal with this issue, this paper proposed a deep learning model for depression identification in social media data which is imbalanced (X-A-BiLSTM) [18]. This model had two fundamental elements: the first is XGBoost, which was applied to decrease data imbalance and the second one was an Attention-BiLSTM neural network, which intensified classification capability [18]. In this experiment, a dataset named The Reddit Self-reported

Depression Diagnosis (RSDD) was taken, which involved around 9000 patients who were diagnosed with a mental disorder [18].

5 EDA – Exploratory Data Analysis:

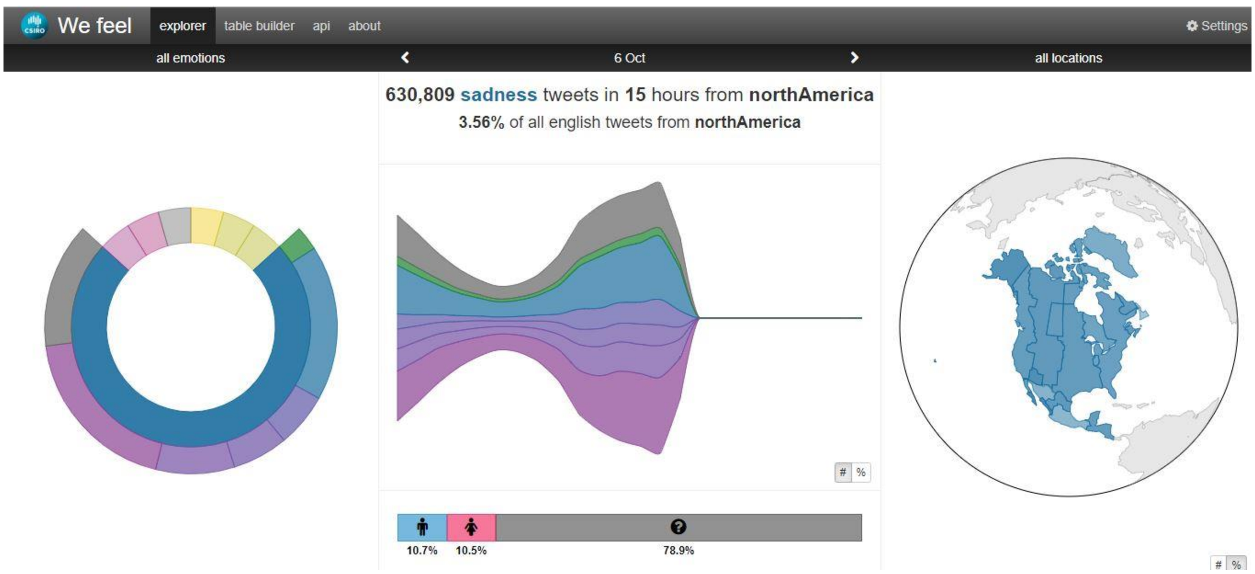
People on Facebook must create accounts under their actual names, and they often connect with their friends and families. Twitter users use fake names to connect with the users which they have never met [2]. This makes Twitter a source of a less biased report of a person's feelings and struggles, as it provides more anonymous means of connection. People undergoing depression, generally may not participate in mental-health-related research, but they tend to share their thoughts and opinions in written form through Twitter [2]. Twitter has an important feature, where it allows users to broadcast news, information, and personal updates to other users in tweets or statements of 140 characters or less [2]. This makes it easy for researchers to collect data that can cover a wide range of tweets. Hence it was clear that Twitter is the best source for this experiment.

5.1 We Feel – a tweet harvesting tool:

While exploring different datasets for depression detection, an interesting tool was discovered, known as 'We Feel'. We Feel system allows real-time study of global and regional changes in emotional expression through Twitter [16].

We Feel attempts to show shifts in mood using three approaches [16].. The first method is, by exhibiting data on daily fluctuations in mood. The second method is, by associating data with predominance data from nations globally to decide if patterns are compatible with these measures The third method is by examining if ‘events of significance’ are correlated with variations in emotional expressions [16].

The system provides an API for non-commercial use, and in extension to that, it provides a web interface that has a series of data visualization choices such as filter by country/time zone level, global, continental, or gender [19] [16].

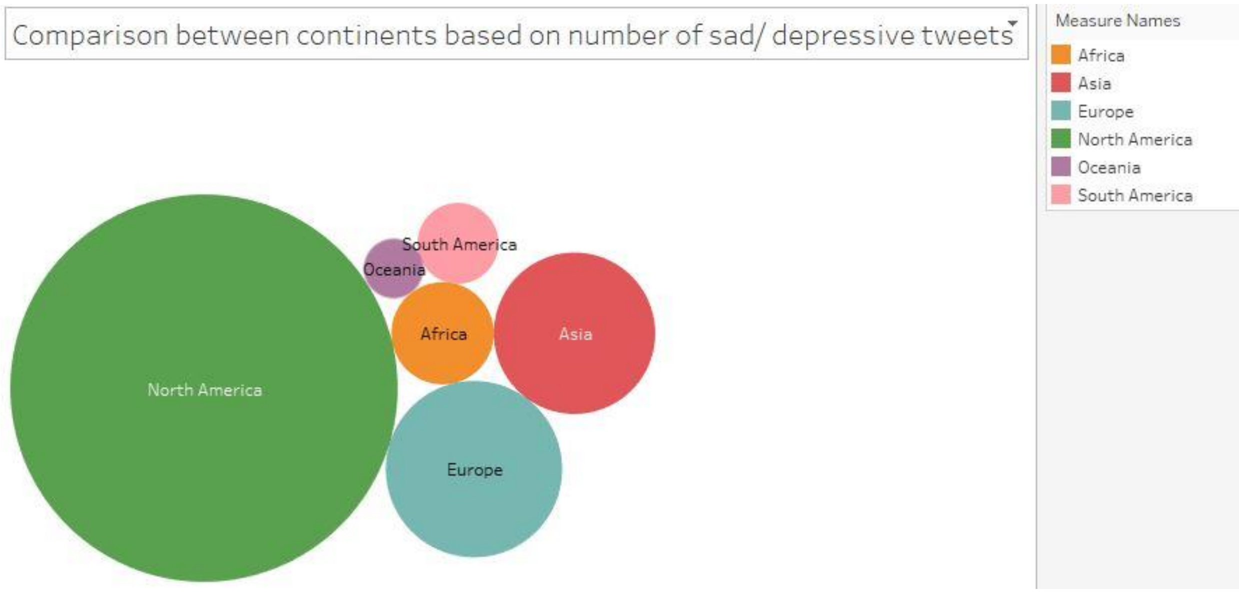


5.1.1.1.1 Figure 1: we feel user interface [19] [16]

Details about the depression analysis performed for this independent study, based on the data obtained from We Feel can be found below [19] [16]:

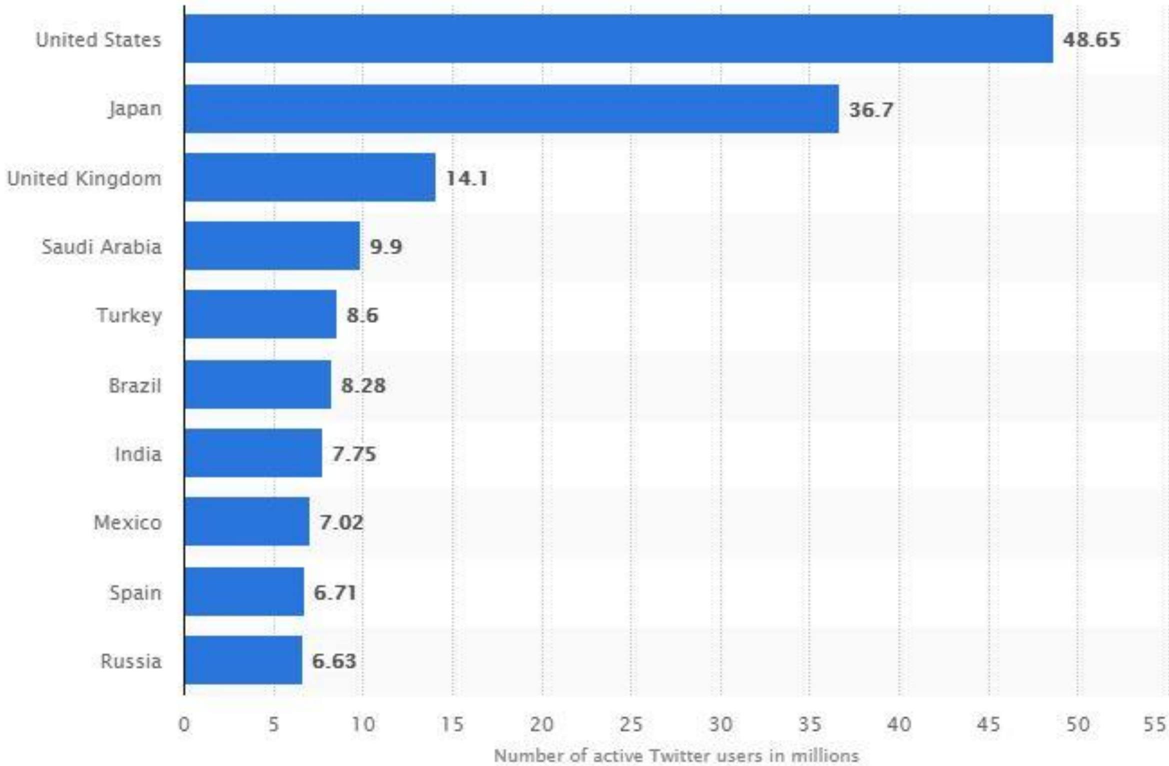
Below visualizations were done by importing the We Feel data in the Tableau [20] tool.

5.1.1 Comparison between continents based on number of sad/ depressive tweets in 2019



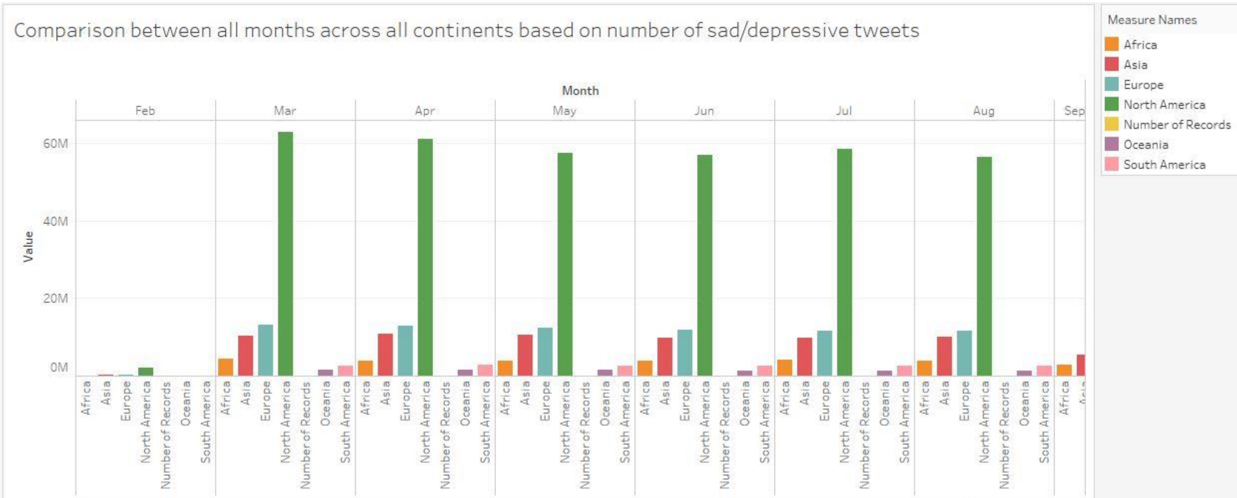
5.1.1.1.1 **Figure 2: Comparison between continents based on number of sad/ depressive tweets in 2019 : It was observed that North America has the highest number of users who have posted sad or depressive tweets, but this could be possible because the United States has the highest number of active users compared to other continents [19] [16]**

It was observed that North America has the highest number of users who have posted sad or depressive tweets, but this could be possible because the United States has the highest number of active users compared to other continents [19] [16]. We can confirm this by looking at the statistics below.



5.1.1.1.2 **Figure 3: Number of Twitter users in different countries: North America has highest number of twitter users [21]**

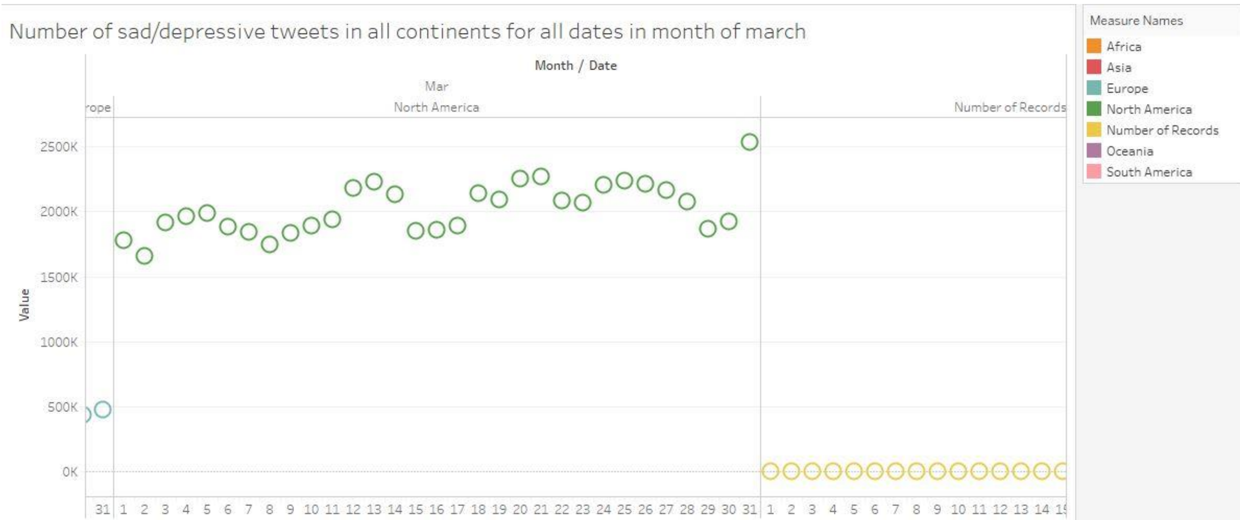
5.1.2 Comparison between all months across all continents based on number of sad/depressive tweets.



5.1.2.1.1 **Figure 4: Comparison between all months across all continents based on number of sad/depressive tweets: The month of March in 2019 has the highest number of depressive tweets.**

As shown, in the chart above, the month of March in 2019 has the highest number of depressive tweets. To find out the reason for this sadness, further investigation was done to get the date at which most depressive tweets were posted.

5.1.3 Number of sad/depressive tweets in all continents for all dates in month of march



5.1.3.1.1 **Figure 5: Number of sad/depressive tweets in all continents for all dates in month of march: Further investigation was done to get the date at which most depressive tweets were posted. 31st March 2019 shows the highest count. Focus was mainly on North America to make the observation less bias**

Here the focus was mainly on North America to make the observation less bias, as North America has the highest number of tweets. As we can see above, 31st March 2019 shows the highest count.

Now, if we look at the news stories on 31st March 2019 [22], we can see that some unfortunate events happened on that day. Such as:

- Man killed, two others injured outside rapper Nipsey Hussle's L.A. store
- South Carolina college reports death of student, 21, a day after she climbed into car she thought was her ride share
- U.S. ending aid to El Salvador, Guatemala, Honduras over migrants

- Judge throws out Trump executive order and restores Obama-era drilling ban in Arctic
- Fox & Friends' displays headline about '3 Mexican Countries'
- Trump moves to cut aid to Central America, amid caravans and flood of refugees
- Fox apologizes for confusing Mexico with Central America
- 3 children reported missing within three miles of each other
- Why didn't Obama do more to counter Russia's interference in our election?
- Dallas Cowboys legend Michael Irvin announces he is cancer-free after scare
- Biden denies acting 'inappropriately' with women, but vows to 'listen respectfully'

5.1.3.1.2 **Figure 6 : Top news stories on 31st March 2019 : shows some unfortunate events happened. [22] [23] [24]**

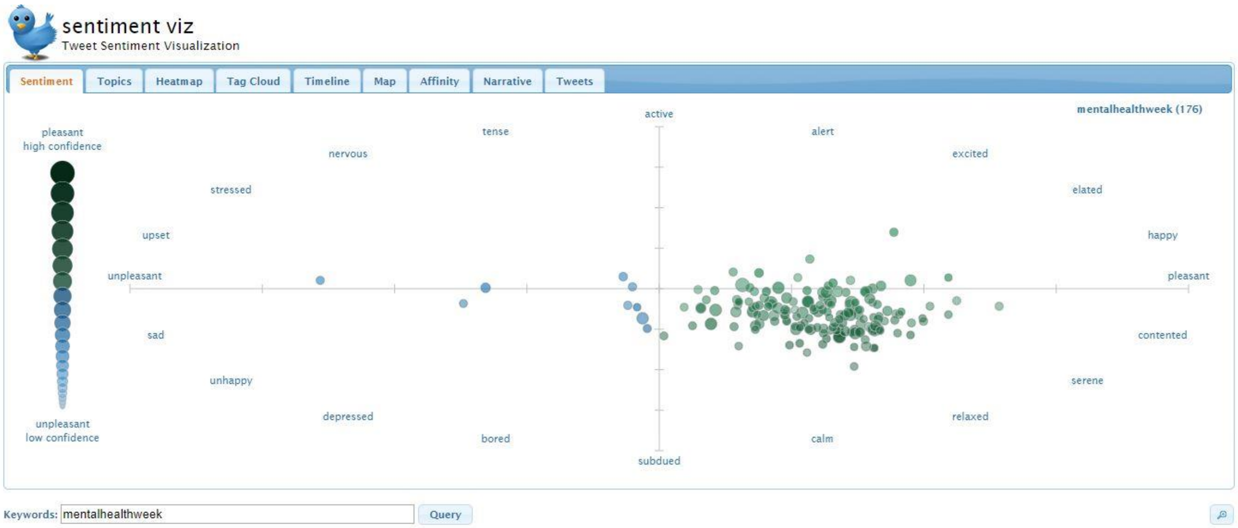
But, just by looking at the news stories of 31st March 2019 day [23] [24], we cannot say that the reason for depressive tweets was based on this, and this is the major drawback of 'We Feel'. Even though, 'We Feel' gives us easy access to counts of tweets based on criteria like emotions, locations, and gender, we cannot see the tweets and find the actual reason behind it.

5.2 Sentiment Viz – a sentiment analysis visualization tool:

Another interesting tool that was helpful for this study was 'NCSU Tweet Sentiment Visualization App'. This application is built by Dr. Christopher Healey who is a Professor at the Institute of Advanced Analytics at North Carolina State University [23] [24]. The tool offers numerous visualization options/tabs that can be explored and some of them are explained below. 'mentalhealthweek' was given as a query input in the tool.

5.2.1 Sentiment Tab:

Here tweets are displayed in circles, and they are placed based on the emotion based on the content represented by the tweet [23] [24].



5.2.1.1.1 **Figure 7: Sentiment Tab Visualization – tweets placed based closer to the emotions specified [23] [24].**

5.2.2 Topics:

Tweets are grouped into clusters based on common themes. Tweets that do not relate to any cluster are displayed in singletons section [23] [24]..

5.2.2.1.1 **Figure 8: Topics Tab Visualization—clusters of tweets based on similarity in emotions [23] [24].**

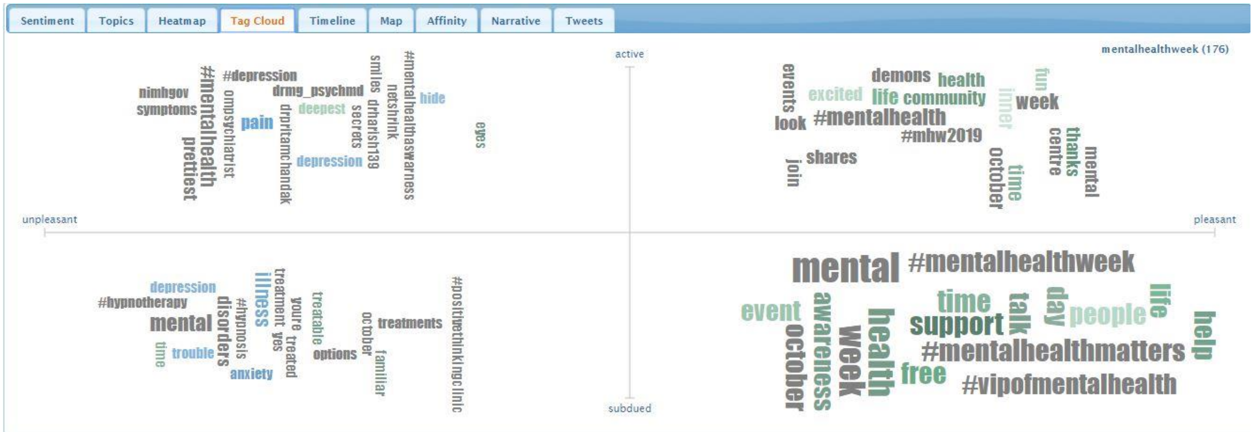
5.2.3 Heatmap Tab:

In the heatmap, the emotions are divided into an 8X8 grid. If the number of tweets is more than average, it is represented by red color whereas for a low number of tweets, the blue color is used [23] [24].

5.2.3.1.1 **Figure 9: Heatmap Tab Visualization—Red (count more than average), Blue (less than average) [23] [24].**

5.2.4 Tag Cloud Tab:

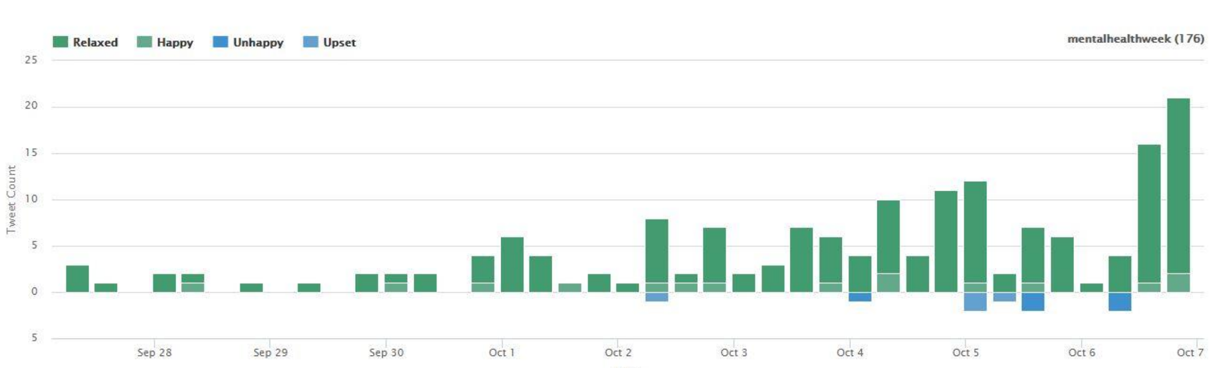
This represents tags that are related to different emotions, the size of the tag depends upon its frequency in the tweets [23] [24].



5.2.4.1.1 **Figure 10: Tag Cloud Tab Visualization – larger size of words shows higher frequency [23] [24].**

5.2.5 Timeline Tab:

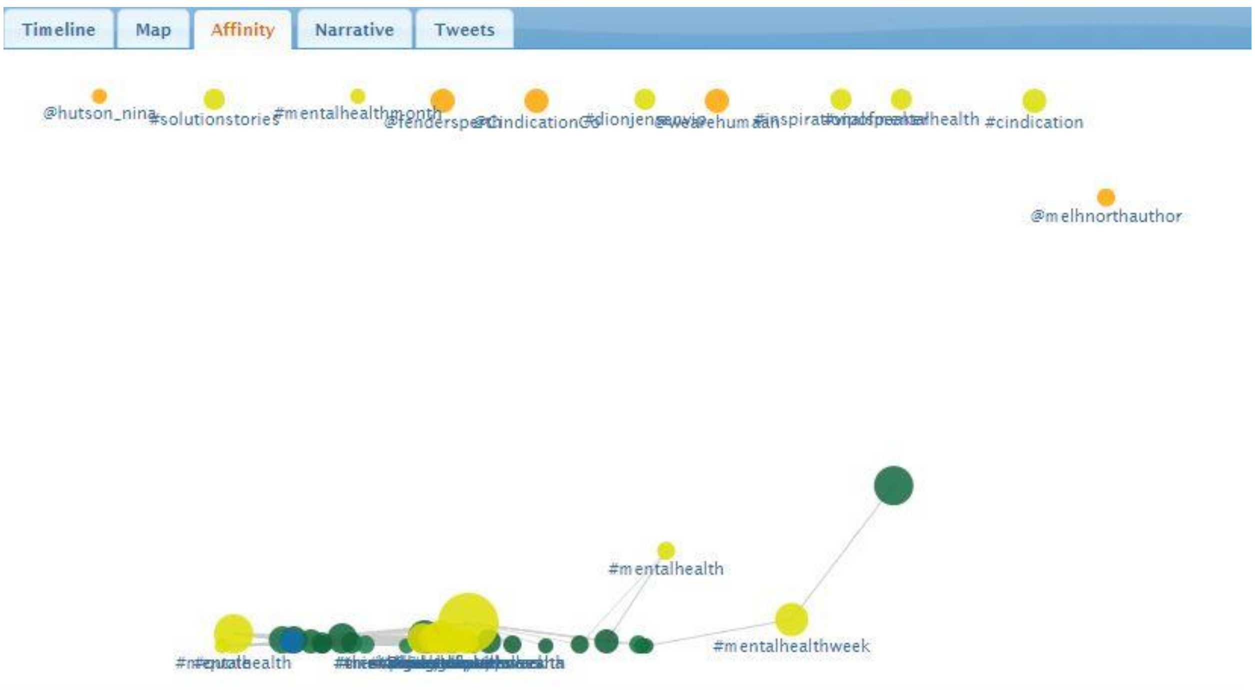
This shows the number of tweets at different times related to different emotions [23] [24].



5.2.5.1.1 **Figure 11: Timeline Tab Visualization—count of tweets for different emotions over time [23] [24].**

5.2.6 Affinity Tab:

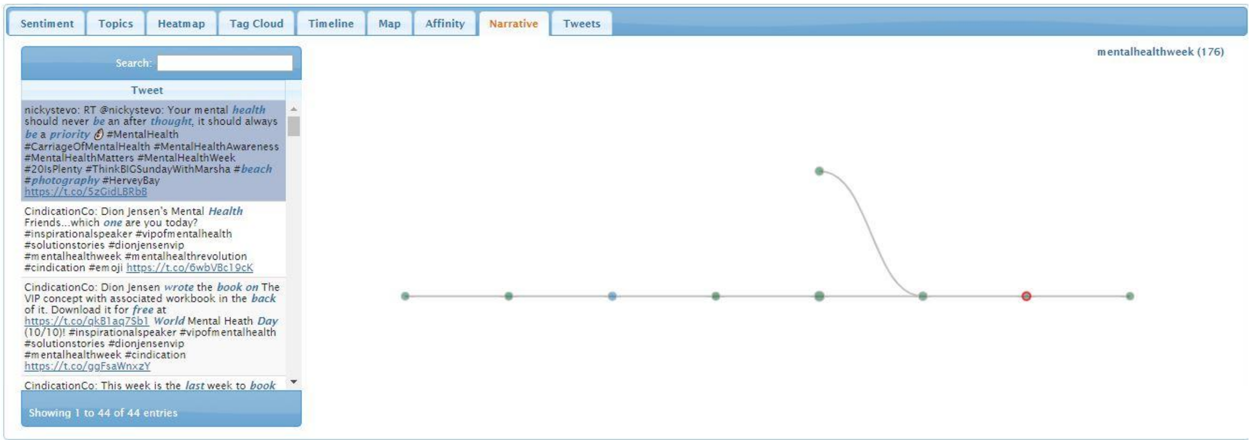
Here, a graph is displayed which shows people, tweets or hashtags which occur regularly and highlights artists in a tweet set and their connection to one another [23] [24].



5.2.6.1.1 Figure 12: Affinity Tab Visualization – shows similarity between different hashtags [23] [24].

5.2.7 Narrative Tab:

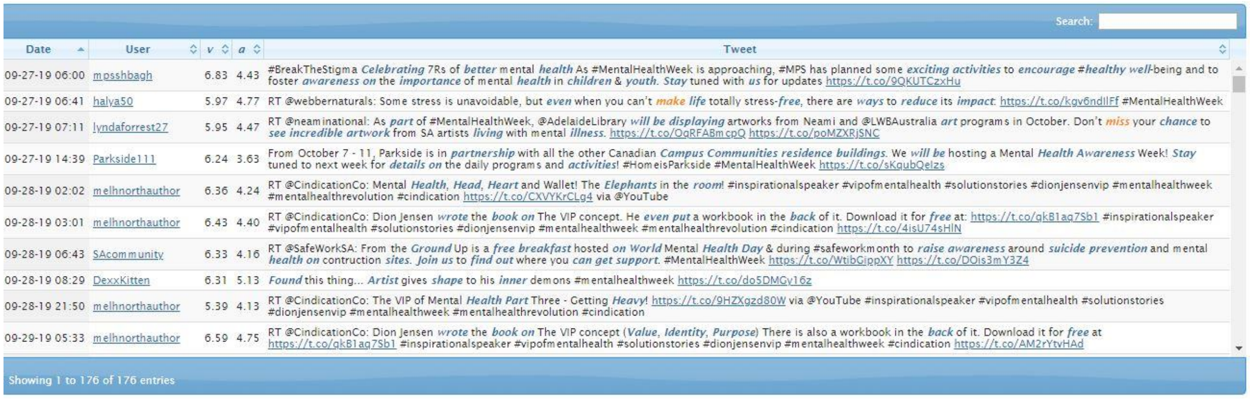
This tab gives an option of selecting an anchor tag and once the tag is selected, chronological threads passing through that thread are shown [23] [24].



5.2.7.1.1 **Figure 13: Narrative Tab Visualization – shows chronological threads passing through selected anchor tag [23] [24].**

5.2.8 Tweets Tab:

This tab lists the tweets related to the query input and details about those tweets such as author, date, etc. [23] [24].



Search:

Date	User	v	a	Tweet
09-27-19 06:00	mpsshbagh	6.83	4.43	#BreakTheStigma Celebrating 7Rs of better mental health As #MentalHealthWeek is approaching, #MPS has planned some exciting activities to encourage #healthy well-being and to foster awareness on the importance of mental health in children & youth. Stay tuned with us for updates https://t.co/9QKUTCzxHu
09-27-19 06:41	halya50	5.97	4.77	RT @webbernaturals: Some stress is unavoidable, but even when you can't make life totally stress-free, there are ways to reduce its impact. https://t.co/kgv6ndIlFf #MentalHealthWeek
09-27-19 07:11	lyndaforrest27	5.95	4.47	RT @neaminational: As part of #MentalHealthWeek, @AdelaideLibrary will be displaying artworks from Neami and @LWBAustralia art programs in October. Don't miss your chance to see incredible artwork from SA artists living with mental illness. https://t.co/OqRFABmcpQ https://t.co/poMZXRjSNC
09-27-19 14:39	Parkside111	6.24	3.63	From October 7 - 11, Parkside is in partnership with all the other Canadian Campus Communities residence buildings. We will be hosting a Mental Health Awareness Week! Stay tuned to next week for details on the daily programs and activities! #HomeisParkside #MentalHealthWeek https://t.co/sKqubQelzs
09-28-19 02:02	melhnorthauthor	6.36	4.24	RT @CindicationCo: Mental Health, Head, Heart and Wallet! The Elephants in the room! #inspirationalspeaker #vipofmentalhealth #solutionstories #dionjensenvip #mentalhealthweek #mentalhealthrevolution #cindication https://t.co/CXVYKrCLg4 via @YouTube
09-28-19 03:01	melhnorthauthor	6.43	4.40	RT @CindicationCo: Dion Jensen wrote the book on The VIP concept. He even put a workbook in the back of it. Download it for free at: https://t.co/qkB1aq7Sb1 #inspirationalspeaker #vipofmentalhealth #solutionstories #dionjensenvip #mentalhealthweek #mentalhealthrevolution #cindication https://t.co/4isU74sHlN
09-28-19 06:43	SAcommunity	6.33	4.16	RT @SafeWorkSA: From the Ground Up is a free breakfast hosted on World Mental Health Day & during #safeworkmonth to raise awareness around suicide prevention and mental health on contruction sites. Join us to find out where you can get support. #MentalHealthWeek https://t.co/WtibGippXY https://t.co/DOis3mY3Z4
09-28-19 08:29	DexxKitten	6.31	5.13	Found this thing... Artist gives shape to his inner demons #mentalhealthweek https://t.co/do5DMGy16z
09-28-19 21:50	melhnorthauthor	5.39	4.13	RT @CindicationCo: The VIP of Mental Health Part Three - Getting Heavy! https://t.co/9HZXgzd80W via @YouTube #inspirationalspeaker #vipofmentalhealth #solutionstories #dionjensenvip #mentalhealthweek #mentalhealthrevolution #cindication
09-29-19 05:33	melhnorthauthor	6.59	4.75	RT @CindicationCo: Dion Jensen wrote the book on The VIP concept (Value, Identity, Purpose) There is also a workbook in the back of it. Download it for free at https://t.co/qkB1aq7Sb1 #inspirationalspeaker #vipofmentalhealth #solutionstories #dionjensenvip #mentalhealthweek #cindication https://t.co/AM2rYtvHAd

Showing 1 to 176 of 176 entries

5.2.8.1.1 **Figure 14: Tweets Tab Visualization—shows tweet and user information [23] [24].**

Based on the above observation, we can conclude that during the 'Mental Health Week', count of pleasant tweets are more than depressive tweets, which shows that more and more people are becoming aware of the issue and they are taking steps towards becoming healthier. But, the foremost issue with this tool is that it cannot handle a large amount of data which makes it inefficient for this study.

After a lot of research, it was realized that there are no openly available datasets comprising 'depressive' Tweets, and it was necessary to create a new dataset for this independent study. The first choice was certainly 'Tweepy', which is a Python library for accessing Twitter API. But we cannot access Tweepy without a developer account, so the model created in this independent study will not be reproducible by anyone interested in rebuilding it.

Ultimately, it was realized that none of the existing datasets are a good fit for this independent study. So, an optimal dataset was created specifically for the study using a combination of TWINT and Kaggle.

6 Dataset Preparation

Data was taken from two different sources to represent two labels, one which represents depressive data and one which does not represent depressive data [25]. TWINT allows easy access to Tweets from Twitter profiles without using Twitter's API, written in Python [26] [27]. So, around 2500 tweets having the keywords such as “Depression”,” Lonely”, “Suicide” was filtered using TWINT and were given a label '1'. Now, to get tweets that are not related to depression, another dataset called Sentiment140 from Kaggle was taken [28] [26] [27]. In the Sentiment140 dataset, the tweets are divided into three types negative (0), neutral (2) and positive (4), based on the content of the tweets [28] [26] [27] [25]. For this independent study, around 10000 random tweets from Sentiment140 were taken to create another label '0' in the newly created dataset [28] [26] [27] [25].

6.1.1 Random Tweets from Kaggle (Sentiment 140) [28]:

Attributes	**Description**
target	The polarity of the tweet (0 = negative, 4 = positive)
ids	the id of the tweet
date	the date of the tweet
flag	The query. If there is no query, then this value is NO_QUERY
user	the user that tweeted
text	the text of the tweet

Dataset sample is shown below:

	0	1467810369	Mon Apr 06 22:19:45 PDT 2009	NO_QUERY	_TheSpecialOne_	@switchfoot http://twitpic.com/2y1zl - Awww, that's a bummer. You shoulda got David Carr of Third Day to do it. ;D
799999	4	1467822272	Mon Apr 06 22:22:45 PDT 2009	NO_QUERY	ersle	I LOVE @Health4UandPets u guys r the best!!
800000	4	1467822273	Mon Apr 06 22:22:45 PDT 2009	NO_QUERY	becca210	im meeting up with one of my besties tonight! ...
800001	4	1467822283	Mon Apr 06 22:22:46 PDT 2009	NO_QUERY	Wingman29	@DaRealSunisaKim Thanks for the Twitter add, S...
800002	4	1467822287	Mon Apr 06 22:22:46 PDT 2009	NO_QUERY	katarinka	Being sick can be really cheap when it hurts t...
800003	4	1467822293	Mon Apr 06 22:22:46 PDT 2009	NO_QUERY	_EmilyYoung	@LovesBrooklyn2 he has that effect on everyone
0	0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by ...
1	0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Man...
2	0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire
3	0	1467811193	Mon Apr 06 22:19:57	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all....

6.1.1.1.1 **Figure 15: Sentiment140 Dataset Sample [25] [28]**

For this independent study, only the tweet and target (Polarity) of the dataset are considered.

6.1.2 Depressive Tweets using TWINT:

The below query was used to extract data between the dates 2019-1-1 and 2019-10-10, using the word “Depression” as a filter [26] [27].

```
!sudo twint --verified -s "Depression" --since 2019-1-1 --until 2019-10-10 --count --limit 2500
```

```
!sudo twint --verified -s   "Depression"  --since 2019-1-1  --until 2019-10-10  --count --limit 5000
```

```
1182079273278099456 2019-10-09 23:43:55 UTC <JimmyGeurts> Gary Gulman's The Great Depresh is well worth watching if you or anyone you know has
1182078055168253953 2019-10-09 23:39:04 UTC <DailyLifeAu> It can take antidepressants up to six weeks to kick in, but findings of one small st
1182076784713572352 2019-10-09 23:34:02 UTC <passioncity> This Sunday, Cumberland + 515 will be together at 515 for all gathering.

Pastor @louiegiglio is bringing a talk called I'm Not Okay...The church's response to a world struggling with fear, anxiety, depression, and s

515 Garson Drive: 9:15a, 11:45a, 5p  pic.twitter.com/n7WETYrGqI
1182076048462229504 2019-10-09 23:31:06 UTC <CTVNews> Depression was ruining a social media star's life. This is how she beat it  http://bit.l
1182070338433306626 2019-10-09 23:08:25 UTC <WEKetchum> Thing is! He doesn't say depression or lesson on the song at all and you still knew
1182069758600105985 2019-10-09 23:06:06 UTC <thenation> Bullying, depression, debt and 90-hour weeks pushed them to walk out of the job.
 http://bit.ly/31WOUAF
1182068477072478214 2019-10-09 23:01:01 UTC <tes> This #WorldMentalHealthDay, @GirlguidingScot has released figures showing that 77% of girls
1182068222763372544 2019-10-09 23:00:00 UTC <them> According to a report from the Human Rights Campaign, queer teens suffer from high rates of
1182068092760756225 2019-10-09 22:59:29 UTC <tonyposnanski> LAST EBAY ON THE NIGHT! I'm auctioning off my second "Love yourself" set. You get
 http://rover.ebay.com/rover/1/711-53200-19255-0/1?icep_ff3=2&pub=5575378759&campid=5338273189&customid=&icep_item=323943294998&ipn=psmain&ice
1182066767683735552 2019-10-09 22:54:13 UTC <georgeinstitute> Join us this #WorldMentalHealthDay to ask for national recognition and to roll c
```

6.1.2.1.1 Figure 16: Twint Query Example [26] [27].

This data was saved in a CSV file and only the column containing tweets were considered for the study, labeled as "1" later in the process.

0	tweet
1	Gary Gulman's The Great Depresh is well worth ...
2	It can take antidepressants up to six weeks to...
3	This Sunday, Cumberland + 515 will be together...
4	Depression was ruining a social media star's l...

6.1.2.1.2 Figure 17: Depressive Tweets Sample [26] [27].

7 Data Cleaning and Preprocessing:

The data obtained from tweets was extremely dirty and contained unnecessary elements. For example, consider the below tweet.

'Battling the symptoms of #depression, is no doubt difficult, but itâ€™s import ant that people understand theyâ€™re not alone. Find out how you can help at http://adaa.orgÂ . #ArmyMedicine pic.twitter.com/5FOXA92Uvk'

The above tweet contains special characters, links, image URLs, unknown characters, numbers, punctuations, stop-words, extra spaces, etc. which are not required and will reduce the machine learning model accuracy. A data cleaning function was created which handles below issues in the tweet.

1. Negation Handling [29]

All the words with apostrophes, such as "aren't" ,"can't", "couldn't" needed to be replaced by their standard lexicons. A dictionary taken from analytics vidhya blog [30] was used to create a function in Python to replace such words. The dictionary is shown below [29].

```
appos = {
"aren't" : "are not",
"can't" : "cannot",
"couldn't" : "could not",
"didn't" : "did not",
"doesn't" : "does not",
"don't" : "do not",
"hadn't" : "had not",
"hasn't" : "has not",
"haven't" : "have not",
"he'd" : "he would",
"he'll" : "he will",
"he's" : "he is",
"i'd" : "I would",
"i'd" : "I had",
"i'll" : "I will",
"i'm" : "I am",
"isn't" : "is not",
```

```
"it's" : "it is",
"it'll":"it will",
"i've" : "I have",
"let's" : "let us",
"mightn't" : "might not",
"mustn't" : "must not",
"shan't" : "shall not",
"she'd" : "she would",
"she'll" : "she will",
"she's" : "she is",
"shouldn't" : "should not",
"that's" : "that is",
"there's" : "there is",
"they'd" : "they would",
"they'll" : "they will",
"they're" : "they are",
"they've" : "they have",
"we'd" : "we would",
"we're" : "we are",
"weren't" : "were not",
"we've" : "we have",
"what'll" : "what will",
"what're" : "what are",
"what's" : "what is",
"what've" : "what have",
"where's" : "where is",
"who'd" : "who would",
"who'll" : "who will",
"who're" : "who are",
"who's" : "who is",
"who've" : "who have",
"won't" : "will not",
"wouldn't" : "would not",
"you'd" : "you would",
"you'll" : "you will",
"you're" : "you are",
"you've" : "you have",
"'re": " are",
"wasn't": "was not",
"we'll":" will",
"didn't": "did not"
}
```

7.1.1 Remove Links [31] :

Removing URLs from the text as they are not required for the further processing. After removal of links the from our example tweet, we will get below output [31]:

Battling the symptoms of #depression, is no doubt difficult, but itâ€™s important that people understand theyâ€™re not alone. Find out how you can help at . #ArmyMedicine pic.twitter.com/5FOXA92Uvk

---

7.1.2 Remove Hashtags, Images, Emojis [31] :

After removal of Hashtags, Images and Emojis the from our example tweet, we will get below output [31] :

Battling the symptoms of , is no doubt difficult, but itâ€™s important that people understand theyâ€™re not alone. Find out how you can help at .

7.1.3 Remove weird characters [31] :

After removal of weird characters such as {â € ™ ≈ € ¥ µ} from our example tweet, we will get below output [31] :

Battling the symptoms of , is no doubt difficult, but it's important that people understand they're not alone. Find out how you can help at .

7.1.4 Remove Contraction/ Negation [31] :

After applying the function created above for handling the contraction, we get the below text:

Battling the symptoms of , is no doubt difficult, but it is important that people understand they are not alone. Find out how you can help at .

7.1.5 Remove Punctuation [31] :

After removal of punctuations such as {!"#$%&'()*+,-./:;<=>?@[\]^_`{|}~} from our example tweet, we will get below output:

Battling the symptoms of is no doubt difficult but it is important that people understand they are not alone Find out how you can help at

---

7.2 Natural Language Processing:

Unlike "Structured" data that can be represented using rows and columns of the relational database, "Unstructured" data is very messy and difficult to handle and parse [32]. Tweets are an example of Unstructured data [32]. Due to the advances in the discipline of machine learning, a new technology has emerged that deals with the issue of handling the Unstructured data, known as Natural Language Processing [32]. Using Natural Language Processing we can perform analysis and processing on the unstructured data, after which the machine can interpret and understand the meaning of the text at least to some extent [33].

7.2.1 Remove Stop-words:

One of the first steps that are performed in Natural Language Processing is Removal of Stop Words. Stop Words are the words used in a text that are not required, such as {and, the, a, an, to, up, etc.}. This was done by importing stopwords library from nltk.corpus. The list of stopwords is shown below [33]:

>>>set(stopwords.words('english'))

{'ourselves', 'hers', 'between', 'yourself', 'but', 'again', 'there', 'about', 'once', 'during', 'out', 'very', 'having', 'with', 'they', 'own', 'an', 'be', 'some', 'for', 'do', 'its', 'yours', 'such', 'into', 'of', 'most', 'itself', 'other', 'off', 'is', 's', 'am', 'or', 'who', 'as', 'from', 'him', 'each', 'the', 'themselves', 'until', 'below', 'are', 'we', 'these', 'your', 'his', 'through', 'don', 'nor', 'me', 'were', 'her', 'more', 'himself', 'this', 'down', 'should', 'our', 'their', 'while', 'above', 'both', 'up', 'to', 'ours', 'had', 'she', 'all', 'no', 'when', 'at', 'any', 'before', 'them', 'same', 'and', 'been', 'have', 'in', 'will', 'on', 'does', 'yourselves', 'then', 'that', 'because', 'what', 'over', 'why', 'so', 'can', 'did', 'not', 'now', 'under', 'he', 'you', 'herself', 'has', 'just', 'where', 'too', 'only', 'myself', 'which', 'those', 'i', 'after', 'few', 'whom', 't', 'being', 'if', 'theirs', 'my', 'against', 'a', 'by', 'doing', 'it', 'how', 'further', 'was', 'here', 'than'}

After removing the stopwords from our example tweet, the tweet looks like below:

Battling symptoms doubt difficult important people understand alone Find help

7.2.2 Stemming:

In Natural Language Processing, Stemming is a process of normalizing the text [34] meaning reducing the different forms of words to their core root. For example, we want our machine to understand that the words ‘smelling’ and ‘smelled’ are originally coming from the verb ‘smell’. So, the idea of Stemming is to convert the word to its original form by removing the tenses or suffixes associated with them [35].

NLTK has different types of Stemming algorithms available:

7.2.2.1 Porter Stemmer:

PorterStemmer removes the suffix associated with the word, for example, ‘dogs’ will get replaced by 'dog'. Results obtained by PorterStemmer might not be in present in actual English, since, words like ‘troubled’, ‘troubling’ get replaced by ‘troubl’. Even though the resultant words are not in English the machine can understand that words with the same stem will have a similar meaning [36].

7.2.2.2 Snowball Stemmer:

Using SnowballStemmer, users can create their own set of rules to perform stemming in any language [36].

7.2.2.3 Lancaster Stemmer:

LancasterStemmer uses an iterative algorithm to decide whether to remove the suffix associated with the word or not [36].

A difference between PorterStemmer and Lancaster Stemmer is shown below [36].

Word	Porter Stemmer	Lancaster Stemmer
friend	friend	friend
friendship	friendship	friend
friends	friend	friend
friendships	friendship	friend
stabil	stabil	stabl
destabilize	destabil	dest
misunderstanding	misunderstand	misunderstand
railroad	railroad	railroad
moonlight	moonlight	moonlight
football	footbal	footbal

7.2.2.3.1 **Figure 18: Difference between Porter Stemmer and Lancaster Stemmer [36]**

For this Independent Study, PorterStemmer is used, and the output of the example tweet is as shown below:

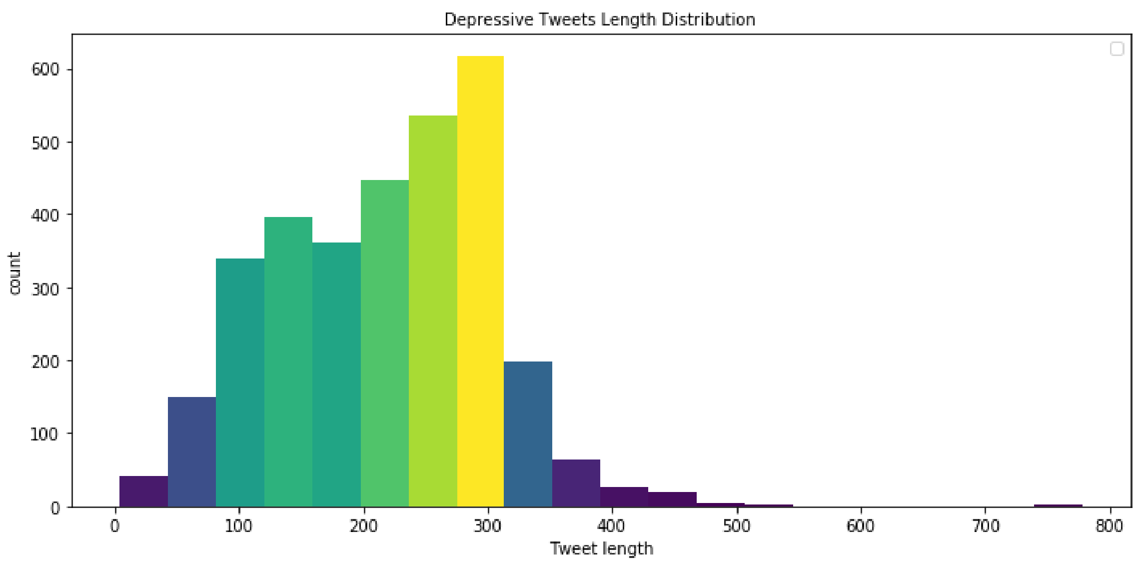
['battl', 'symptom', 'doubt', 'difficult', 'import', 'peopl', 'understand', 'alon', 'find', 'help']

8 Data Visualization:

8.1 Data Distribution:

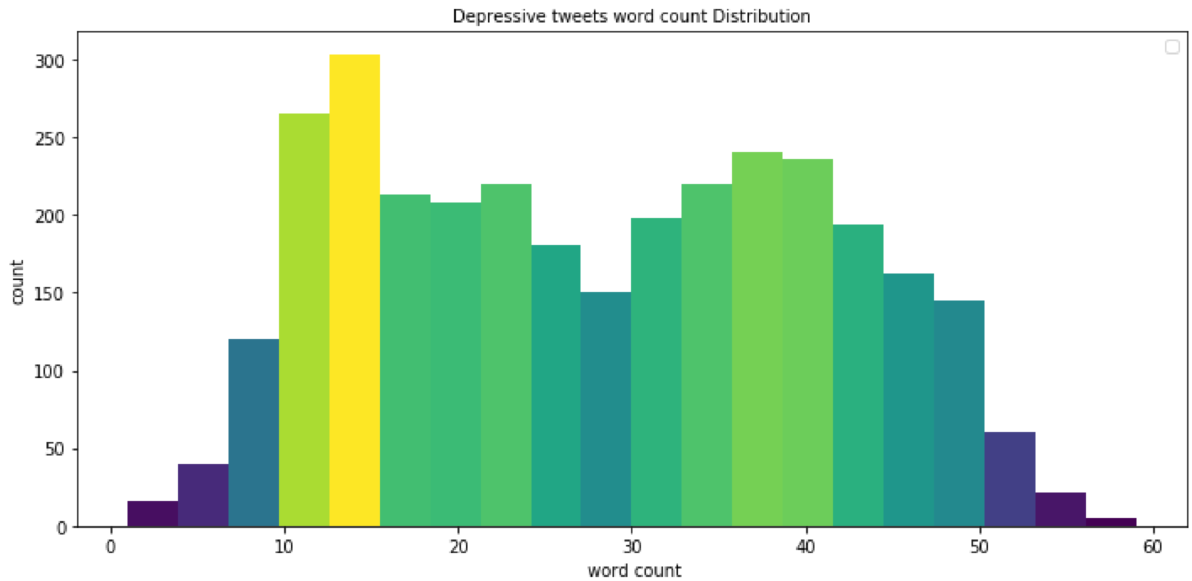
The data was visualized to get an idea of the overall distribution of the length of the tweets and count distribution of words in the tweet, in both, depressive and random data. Libraries like Pandas [37] and Matplotlib [38] were used in Python for the plotting.

1. Depressive Tweets Length Distribution:



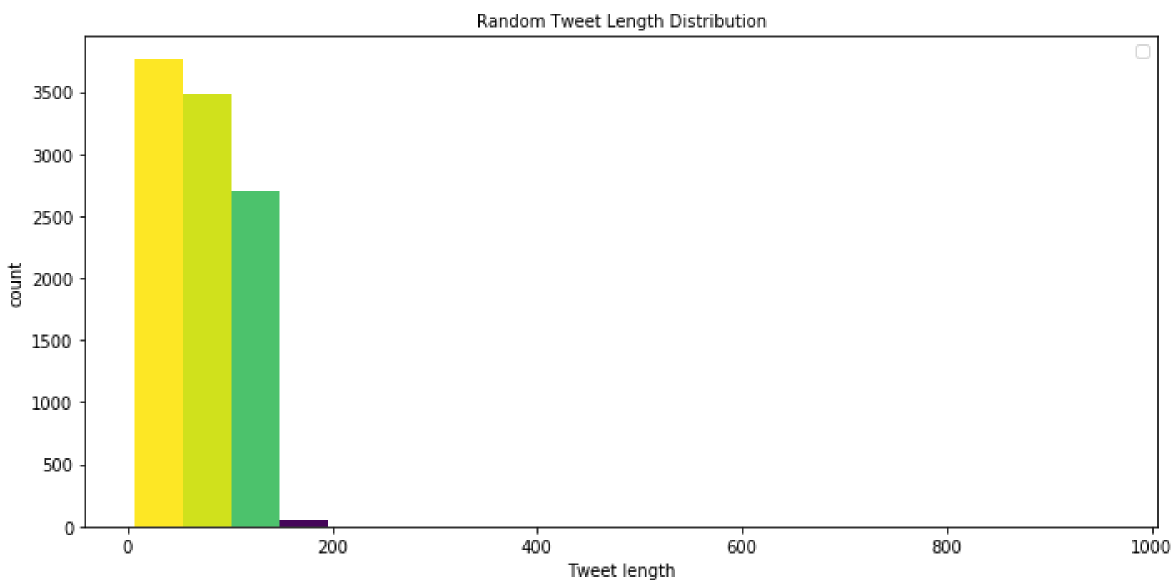
8.1.1.1.1 **Figure 19: Depressive Tweets Length Distribution [37] [38]**

8.1.2 Word Count Distribution in Depressive Tweets:



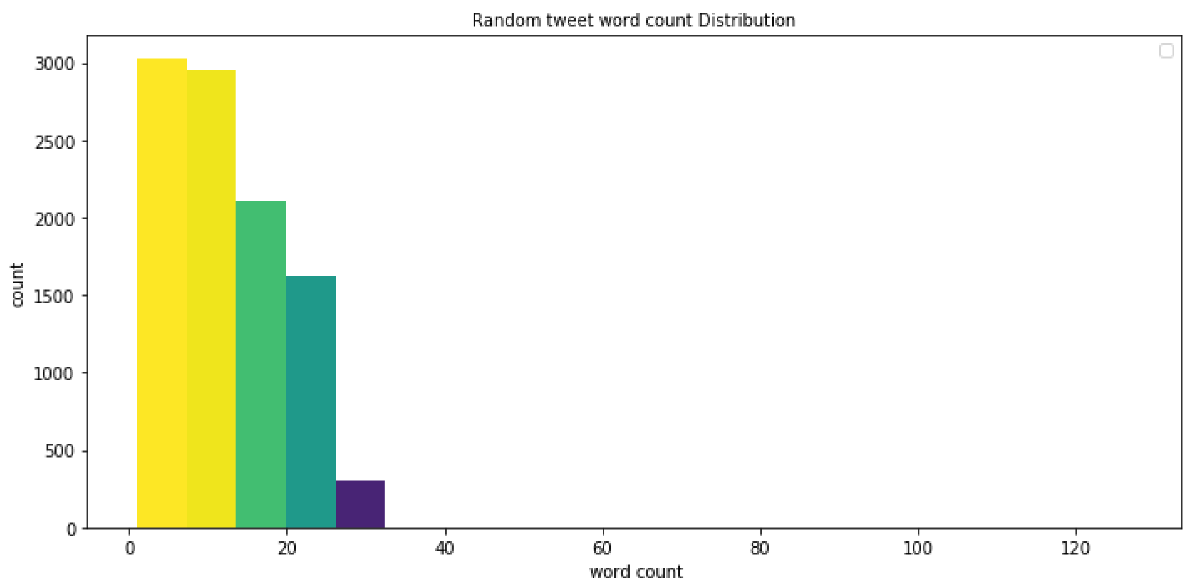
8.1.2.1.1 Figure 20: Word Count Distribution in Depressive Tweets: to get and idea of number of words present in a tweet [37] [38]

8.1.3 Random Tweets Length Distribution:



8.1.3.1.1 Figure 21: Random Tweets Length Distribution [37] [38]

8.1.4 Word Count Distribution in Random Tweets



8.1.4.1.1 **Figure 22: Word Count Distribution in Random Tweets [37] [38]**

8.2 WordClouds/ TagClouds:

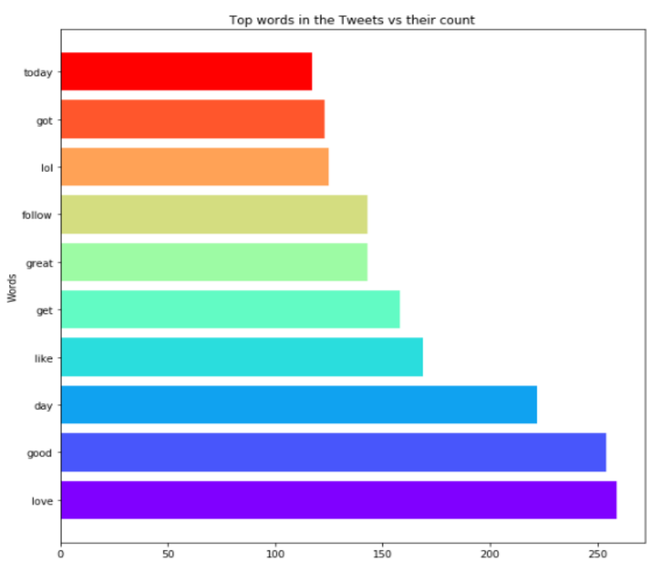
It is not easy to represent the textual data in the form of a graph or a chart where we can convey the important information present in the data. In such cases, WordClouds also known as TagClouds come to the rescue. WordClouds show us a cluster of words present in our data in different sizes and different formats. Here, if a word is bigger and bolder than other words, then it carries higher weight, or the word is used more frequently in the text than other words [39]. For this Independent study, it was necessary to see what are the words which are used most frequently by the users who have posted happy tweets versus the users who have posted sad or depressive tweets [39].

Below the WordClouds of positive data and Depressive data used for the study are represented. Libraries like Pandas, Matlplotlib and Wordcloud were used for creating the WordClouds [40].

1. **Positive Data WordCloud:**

8.2.1.1.1 **Figure 23: Positive Data WordCloud (Larger size shows higher frequency of the word the text) [40].**

Using the above WordCloud, top ten words present in the positive data were plotted, as shown:

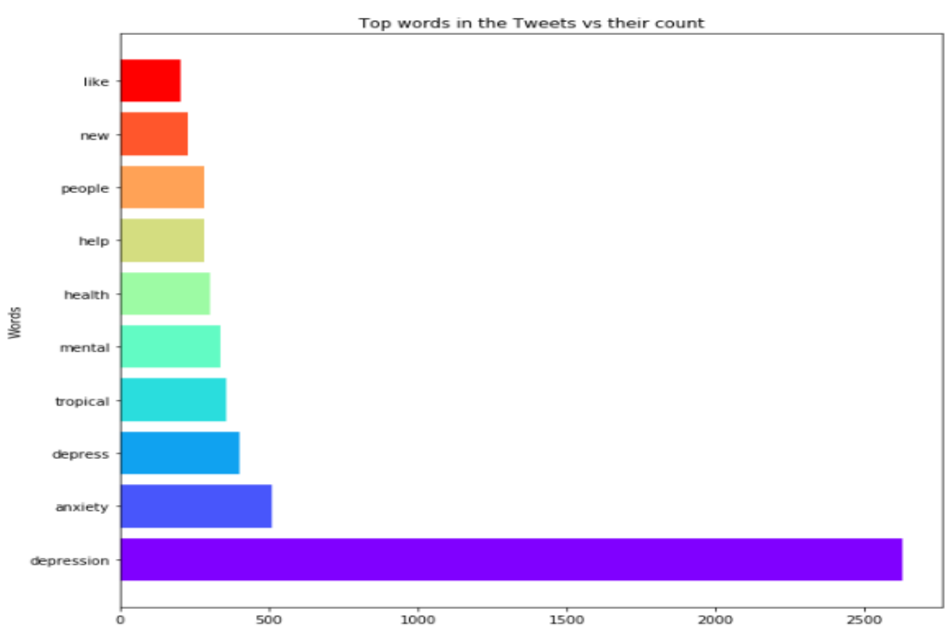


8.2.1.1.2 **Figure 24: Top Ten Words Present in The Positive Data: Words like 'love', 'good', 'day' have higher frequency**

8.2.2 Depressive Data WordCloud:

8.2.2.1.1 **Figure 25: Depressive Data WordCloud (Larger size shows higher frequency of the word the text) [40].**

Using the above wordcloud, top ten words present in the depressive data were plotted, as shown:



8.2.2.1.2 **Figure 26: Top Ten Words Present in The Depressive Data: Words like anxiety, health, mental have higher frequency. Words like depression can be ignored as the dataset was created by filtering the tweets using word the "depression"**

9 Tokenizer:

The Tokenizer class is one of the utilities of the preprocessing module present in Keras API. The class processes the text in two distinct ways, one where the text is converted into a sequence of integers, where the integers come from indexes assigned to tokens in a dictionary [41]. In the second method, the text is converted into a vector where different methods like tf-idf (term frequency-inverse document frequency), word count, etc. are used to define the coefficient associated with the token [41].

For the independent study, the first method is used, where 'tokenizer.text_to_fit' function is used to convert each word in the text into an 'index: token' form based on the frequency of that word in the text and placed into a dictionary [41].

In the below code, cleaned tweets from both depressive and random data are given as input and a dictionary of tokens and indexes is formed [42].

```
tokenizer = Tokenizer(num_words=MAX_NB_WORDS)
tokenizer.fit_on_texts(X_d + X_r)
tokenizer.word_index
```

Output: (first fifty tokens are shown below)

{'i': 1,
'depression': 2,
'like': 3,
'day': 4,
'get': 5,
the': 6,
'anxiety': 7,
'it': 8,
'one': 9,
'good': 10,
'today': 11,
'go': 12,
'new': 13,
'know': 14,
'people': 15,
'depress': 16,
'love': 17,
'got': 18,
'help': 19,
'time': 20,
'tropical': 21,
'great': 22,
'work': 23,
'want': 24,
'mental': 25,
'really': 26,
'u': 27,
'going': 28,
'back': 29,
'im': 30,
'health': 31,
'na': 32,
'would': 33,
'3': 34,
'sad': 35,
'a': 36,
'my': 37,
'see': 38,
'think': 39,
'feel': 40,
'need': 41,
'still': 42,
'lol': 43,
'last': 44,
'could': 45,

'miss': 46,
'much': 47,
'this': 48,
'night': 49,
'well': 50,
………}

In above method the indexes are ordered based on the frequency of the words, so the most frequent words come first in the list. Only the first 20000 frequent tokens are considered, for this study. The fit_on_text function is always followed by the text_to_sequences method, which replaces the word in the text with its corresponding index value [43].

So, the first sentence of the depressive text would now look like below:

[8,63, 2212, 1137, 426, 1332, 2475, 9, 732, 193, 5975, 3734, 660, 19, 2476, 222, 2, 159, 427, 56]

10 Embedding Matrix:

Embedding Matrix is mainly used to define the relationship between the words present in the text [44]. . Imagine that we could map all meaning into a 3D space, such that every word could be represented as a point in that 3D matrix [44]. But it is not possible as, 'meaning' is too complicated to be captured in a 3D space, typically a 300D space is used represent such matrix where a word belongs to some point in this hyperspace [44]. . In other words, these words are represented by 300 numbers (embeddings) [44]. Here, the correlation between the words is expressed by taking their difference (word1 -word2). An example of Embedding Matrix is shown below [44]:

$$
\begin{array}{l}
\text{hello} \\
\text{there} \\
\text{texas} \\
\text{world} \\
\ldots
\end{array}
\begin{bmatrix}
12 & 45 & 43 & 26 & 78 & 532 & \ldots \\
43 & 25 & 778 & 43 & 53 & 78 & \ldots \\
34 & 56 & 23 & 12 & 56 & 74 & \ldots \\
342 & 54 & 23 & 5 & 7 & 423 & \ldots \\
\ldots & & & & & &
\end{bmatrix}
$$

10.1.1.1.1 Figure 27: Embedding Matrix [44]

Embeddings need to be trained like any other deep learning method. The difference between the deep learning models and embedding training is that, the real embeddings are not available, hence the loss/error cannot be calculated using a cost function [44] . So, the embedding matrix is randomly initialized, and a model is trained to guess the context of the word using which a cost is calculated and the weights in the embedding matrix are adjusted [44].

To perform tasks related to Embedding Matrix, a Python library called ‘Gensim’ [45] is used for this Independent Study. “KeyedVectors” utility of Gensim for training the model and to import an existing file from Google word2vec to initialize the initial vectors [45].

```
wvmodel = KeyedVectors.load_word2vec_format(“GoogleNews-vectors-negative300.bin.gz”, binary=True)
```

Now, the trained model can be used to perform various tasks like finding the similarities between two words using .similarity or .distance to find out the distance between two words [45]. Here, .vocab is used to get all the words from the text that is available in the model's vocabulary to create the Embedding Matrix [25].

11 Train/Validation/Test Split:

The sklearn library was used to split the data into Train, Validation and Test sets. The data was first split into train and test with test size 0.2 and then the train data was split into train and validation again with test size 0.2 [46].

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=1)

X_train, X_val, y_train, y_val = train_test_split(X_train, y_train,
test_size=0.2, random_state=1)
```

This gives a ratio of 60:20:20 for train:validation:test data [46].

12 Model Building

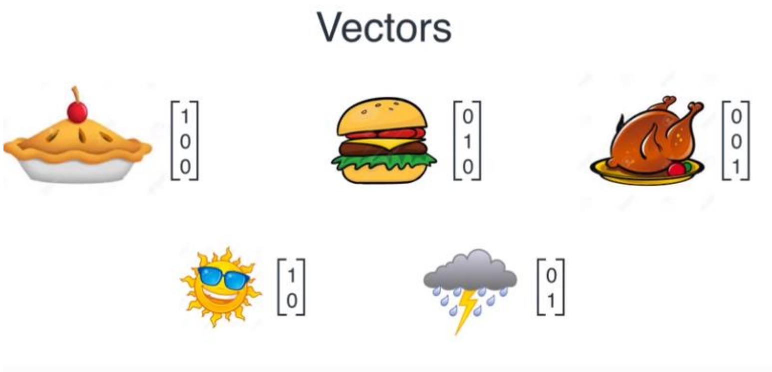
The idea of this Independent Study, that is "Depression Detection Using Tweets" is based on the concept called Text Sentiment Analysis that is one of the most significant researches in the field of Natural Language Processing. This technique involves text preprocessing, text representation, and classifier training [47] [48] [49].

Even though currently the traditional statistical machine learning algorithms have shown good results for text classification [50], they tend to ignore the context of the text, the semantics of capturing the words is not up to the mark and issues like dimension explosion and data sparseness in feature extraction still exist. This lowers the generalization ability of the model to handle complex classification problems [49] [48]. On the other hand, deep learning methods like Convolutional Neural Network [51], Recurrent Neural Network [52], Recursive Neural Network [53] that are generally used for Image Classification or Speech Recognition, have surprisingly performed better than the traditional methods like Support Vector Machine [54], TF-IDF [55], and LDA [56] for text classification.

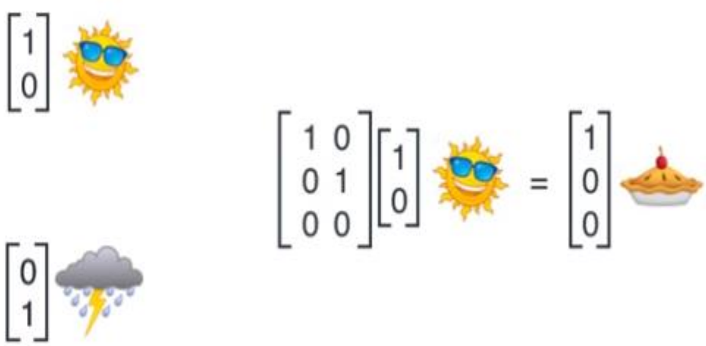
For this Independent Study, a combination of LSTM and CNN is used as LSTM overcomes some of the drawbacks related to RNN. Let’s see the working of both RNN and LSTM and why LSTM is important.

12.1 Recurrent Neural Network (RNN)

Luis Serrano [57] explains RNN in the easiest way possible, by showing an example of a perfect roommate. The roommate cooks three times a day, depending on the weather outside. If it is sunny outside, he cooks apple pie and if it is rainy, he cooks a burger. This can be represented by a simple Neural Network where if we think about the input and output in vector form [57]. Now if the input is a sunny day [1 0], then output is apple pie [1 0 0] and if the input is rainy day [0 1] the output is burger [0 1 0]. Now if we multiply these inputs with an intermediate vector [[1 0] [0 1] [0 0]], we will get the respective outputs [57].



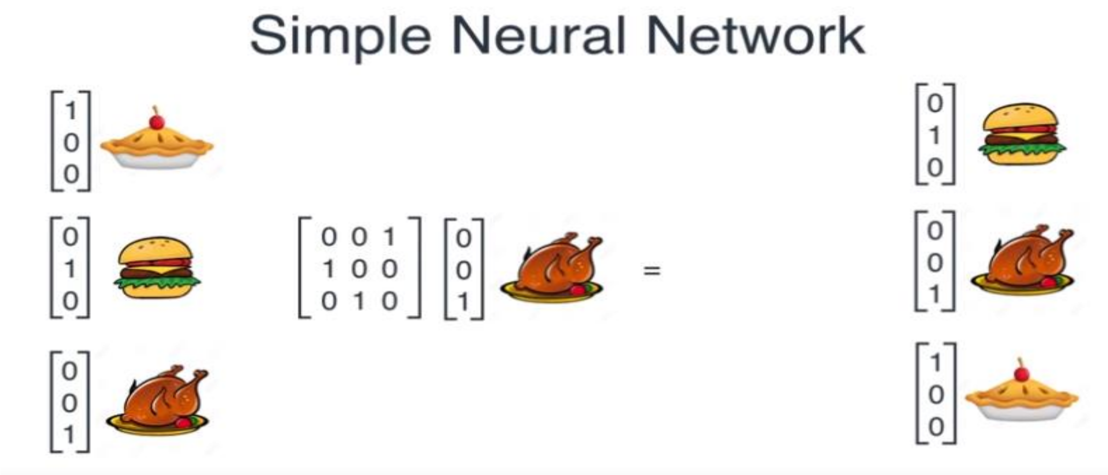
12.1.1.1.1 **Figure 28: Vector Representation of Items [57]**



12.1.1.1.2 **Figure 29: If Input is Sunny, Output is a Pie [57]**

1.1.1.1.1 **Figure 30: If Input is Rainy, Output is a Burger [57]**

Now, the roommate decides to cook in a sequence. So, today if the roommate decides to cook apple pie, tomorrow he will cook a burger, and the next day he will cook chicken. Thus, this is not a normal neural network anymore as the input depends on the previous output, now this becomes a simple recurrent neural network [57].



12.1.1.1.3 **Figure 31: Example of a Simple Recurrent Neural Network [57]**

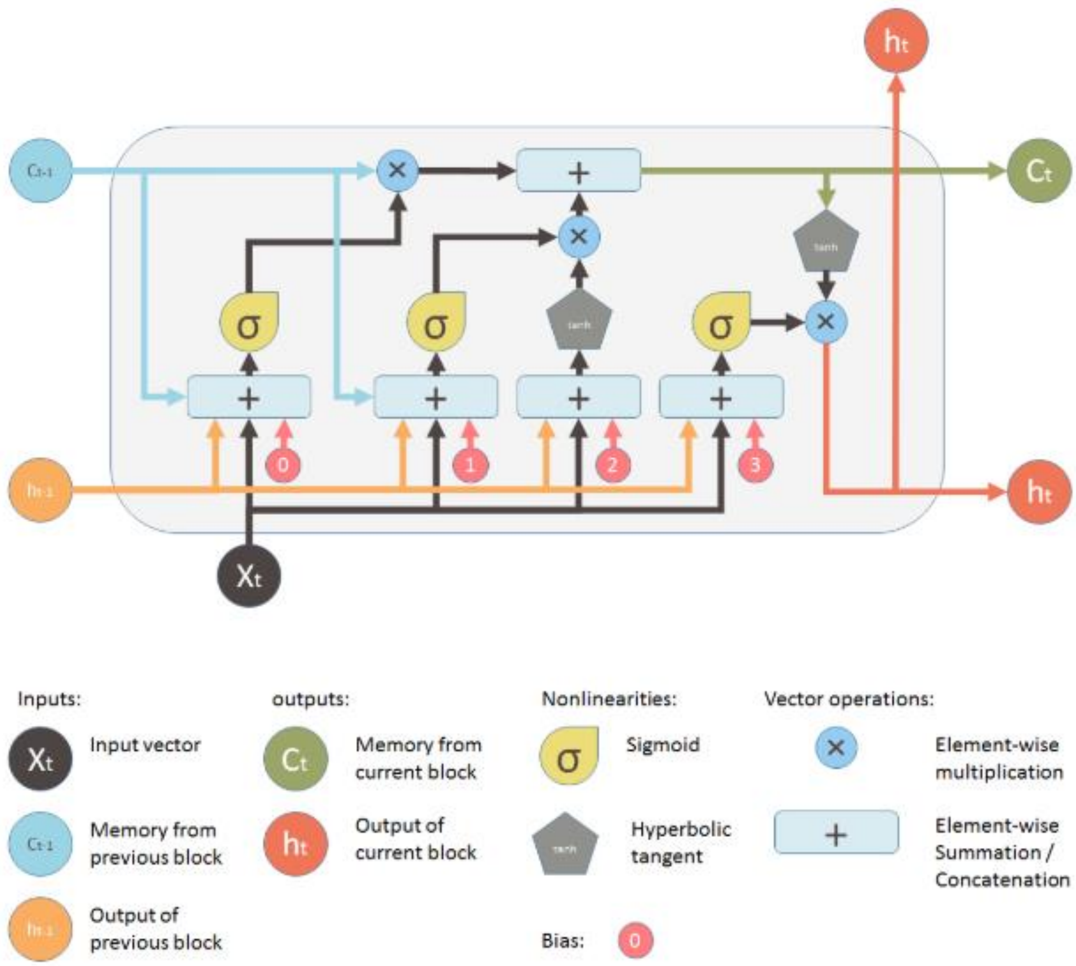
We can convert this problem into a complicated neural network if we combine the previous two rules [57]. For instance, if it is sunny outside, the roommate will not cook and he will serve what was cooked yesterday, but if it is rainy outside, he will cook the next dish in the sequence i.e. the burger. Now, if we observe, we can see that there are two types of inputs, one is the weather and other input is coming from previous state's output and the intermediate vectors would be the combination of food and weather vectors [57].

The major obstacle of RNN is the 'Short Term Memory'. Michel Nguyen describes how the long sequence of RNN could make it forget information from preceding steps. For example, if we are processing a large passage of text for predictions, RNN might leave out some valuable information from the start as during backpropagation the RNN experiences ‘Vanishing Gradient’ problem. During backpropagation, the gradient starts to contract and becomes very small, and as a result, does not learn so much [58].

12.2 Long Short-Term Memory (LSTM)

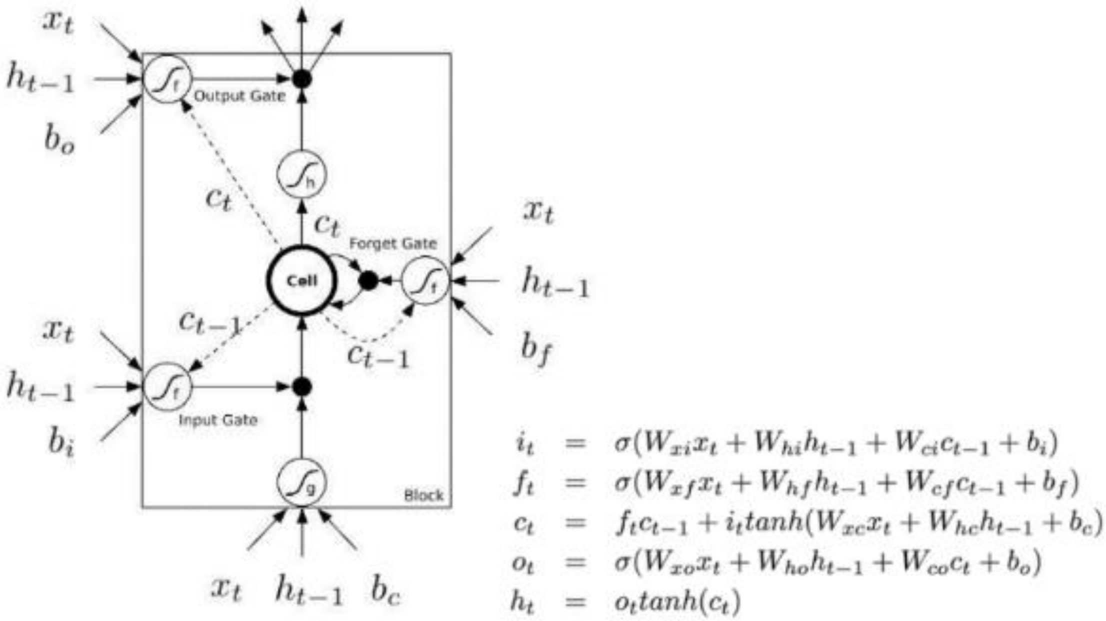
A modified version of RNN known as LSTM (Long Short-Term Memory), is used to overcome the issues related to RNN. Apart from the operations that are performed inside the LSTM cells, the control flow of LSTM is the same as the RNN. These new operations help LSTM in forgetting the less important information [58].

The major components of LSTM are the cell state and its different gates [58]. The cell state is called the memory of the system, where relative information is transferred through the sequence of



12.2.1.1.1 **Figure 32: Long short-term memory (LSTM) Structure [59] [60]**

states [58]. The important information throughout the processing of the sequence is stocked by the cell state which subdues the effect of short-term memory. The information is added or deleted from the cell state using the gates [58]. The gates are different neural networks that learn over the time that which information is necessary and which information has to be deleted [58]. The gates use a combination of sigmoid and tanh activation functions [58].



12.2.1.1.2 **Figure 33:Visual Representation of Input Gate, Forget Gate and Output Gate [60]: Forget gates are used to decide whether to keep information from previous state [58]. Input gates are used to decide which information to keep from current state and output gate is used to decide the next hidden state [58].**

There are three different types of gates, forget gate, input gate and output gate, for three different tasks. Forget gates are used to decide whether to keep information from previous state [58]. Input gates are used to decide which information to keep from current state and output gate is used to decide the next hidden state [58].

12.3 Model Structure

A model containing sequential layers of embedding, convolutional, max-pooling, dropout, and LSTM using Keras [61] was created as shown below [25]:

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 140, 300)          6000000
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 140, 32)           28832
_________________________________________________________________
max_pooling1d_2 (MaxPooling1 (None, 70, 32)            0
_________________________________________________________________
dropout_3 (Dropout)          (None, 70, 32)            0
_________________________________________________________________
lstm_2 (LSTM)                (None, 300)               399600
_________________________________________________________________
dropout_4 (Dropout)          (None, 300)               0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 301
=================================================================
Total params: 6,428,733
Trainable params: 428,733
Non-trainable params: 6,000,000
```

12.3.1.1.1 **Figure 34: CNN-LSTM Model Structure Used for the Study [25]**

A combination of CNN and LSTM exceeds the drawbacks of the individual models [62]. As, CNN is good at handling the local response from temporal or spatial, but it is not good at handling sequential correlations, whereas RNN is good with sequential modeling but does not extract features parallelly [62]. Hence the combination of CNN-LSTM beats their limitations as well as the performance of most of the baseline models [62].

13 Results and Findings:

The above model gave an accuracy of 99.05%.

1. Precision-Recall

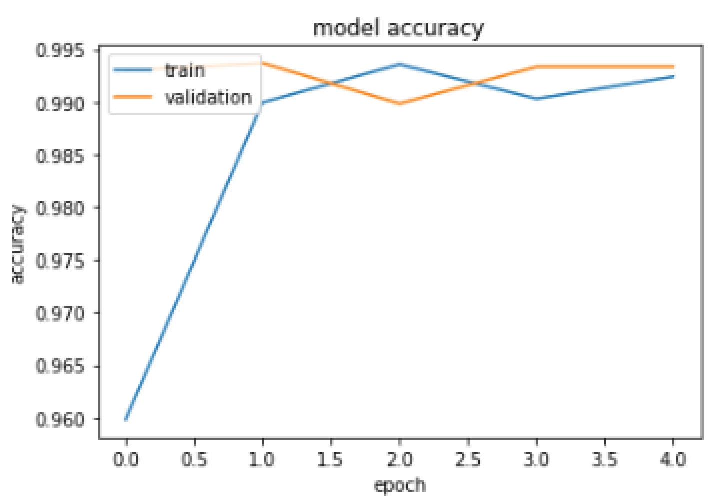
The precision recall report for the model is shown below. The sklearn library in Python was used for generating the report.

	precision	recall	f1-score	support
0	0.99	1.00	0.99	2382
1	0.99	0.95	0.97	462
accuracy			0.99	2844
macro avg	0.99	0.97	0.98	2844
weighted avg	0.99	0.99	0.99	2844

13.1.1.1.1 Figure 35: Precision-Recall Report for the Model Built [25]

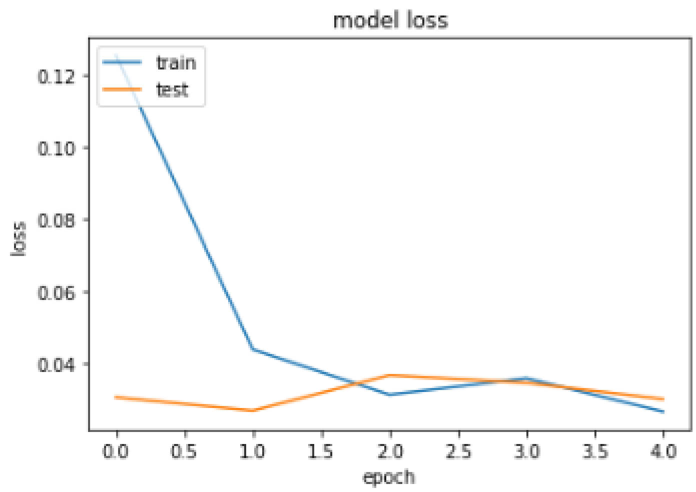
13.1.2 Accuracy-Loss Visualization

Below graph shows the accuracy for training and validation data at each epoch.



1.1.1.1.2 Figure 36:Accuracy of Training and Validation data at each Epoch : the accuracy of training data increases at start and then becomes constant and matches with the accuracy of validation data [25]

Below graph shows the loss for training and validation data at each epoch.



13.1.2.1.1 Figure 37: Loss of Training and Validation data at each Epoch: the loss of training data decreases at start and then becomes constant and matches with the loss of validation data

14 Things Learned

The motivation for the independent study came from the course Seminar in Data Management (CSCI 529) taught by Professor Thomas Kinsman. The seminar helped in understanding different methods for analyzing the social network. This course was based on the book "Analyzing the Social Web" [63], which focuses on different techniques of social network analysis and their applications. [63] not only covers the background and overview of important types of analysis but also introduces different network visualization tools such as Gephi and

NodeXL. Each topic of this book was presented and discussed by the students in the class which gave me a deeper and wider understanding of the subject.

15 Future Work

For this independent study, the data was taken randomly, irrespective of the location. In future, the model can be applied to find out students suffering from depression in Rochester Institute of Technology. A pipeline could be created in AWS (Amazon Web Services) or GCP (Google Cloud Platform) where a tweet and user information can be passed as input and results related to the respective user could be saved in a database. This could help in tracking down the user, who needs help.

16 Conclusions

The goal of this independent study was to identify people suffering from depression using data available from social media. Twitter was chosen as the best option for the collection of data due to the reasons like character limit, and willingness of people to share their feelings in public on twitter. Different tools were explored during this independent study that is addressing the depression detection problem such as “We Feel” and “Sentiment Viz”. We Feel is a great source for visualizing real-time Twitter data and provides different parameters like gender, location, date, time zone, etc. using which users can filter the data. The issue with We Feel is that we can only see the count of tweets related to the search and cannot see the tweet. So, there is no way to validate the assumptions that we have made by looking at visualization or tweet count for a set of parameters. Another important tool related to the study was Sentiment Viz. which provides a great interface to the user, where based on a query, the tool estimates and visualizes sentiments of the tweets. User can see the different forms of graphs where the tweets are segregated based on their level of pleasantness-unpleasantness and activity and inactivity. Again, the issue with Sentiment Viz is that it does not handle a large amount of data.

So, an attempt to create a deep learning model, which will help in the prediction of depressive tweets was made. As data for depressive tweets is not readily available online, a Tweeter scraping tool called ‘TWINT’ was used to collect the depressive tweets and was given the label 1. Another set of data available on Kaggle called ‘Sentiment140’ which provides labeled data for positive and negative sentiments was used and was given the label 0. This data was visualized using Word-Cloud to see the frequency of important words in the data. Frequency of the word ‘Depression’ was found to be most common in the depressive tweets and frequency of the word “Love” was most common in the positive data. Various data cleaning and preprocessing techniques including Natural Language Processing were used before building the model. The model was created using a combination of CNN and LSTM which outperforms not only their individual drawbacks but gives better accuracy than the traditional algorithms, known for text classification. An accuracy of 99.05% was achieved with this experiment.

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18 Appendix- Timesheet

Week	Date	TimeIn	TimeOut	Total Hours	Task
1	Tuesday, August 27, 2019	13:00	14:00	1:00	Meeting with Dr. Kinsman
1	Tuesday, August 27, 2019	14:00	15:15	1:15	Attend CSCI 529 class
1	Wednesday, August 28, 2019	16:00	19:00	3:00	Proposal Writing
1	Tuesday, August 27, 2019	14:00	15:15	1:15	Attend CSCI 529 class
1	Friday, August 30, 2019	10:30	11:00	0:30	Meeting with Dr. Kinsman
1	Friday, August 30, 2019	15:30	17:03	1:33	Finalizing Proposal
1	Saturday, August 31, 2019	13:30	15:00	1:30	Explore different use cases
2	Monday, September 2, 2019	10:00	12:30	2:30	Explore social networking sites Search and read research papers
2	Tuesday, September 3, 2019	14:00	15:15	1:15	Attend CSCI 529 class
2	Wednesday, September 4, 2019	14:00	15:15	1:15	Background Info - Reading Research papers
2	Thursday, September 5, 2019	14:00	15:15	1:15	Attend CSCI 529 class
2	Friday, September 6, 2019	10:30	11:00	0:30	Meeting with Dr. Kinsman
2	Friday, September 6, 2019	17:00	20:00	3:00	Background Info - Reading Research papers
2	Saturday, September 7, 2019	13:30	15:00	1:30	Background Info - Reading Research papers

3	Monday, September 9, 2019	17:45	20:45	3:00	Background Info - Reading Research papers
3	Tuesday, September 10, 2019	14:00	15:15	1:15	Attend CSCI 529 class
3	Wednesday, September 11, 2019	17:00	20:20	3:20	Literature Review
3	Thursday, September 12, 2019	14:00	15:15	1:15	Attend CSCI 529 class
3	Thursday, September 12, 2019	17:00	21:00	4:00	Literature Review
3	Friday, September 13, 2019	10:30	11:00	0:30	Meeting with Dr. Kinsman
3	Friday, September 13, 2019	17:00	20:20	3:20	Literature Review
3	Saturday, September 14, 2019	13:30	15:00	1:30	Literature Review
4	Tuesday, September 17, 2019	14:00	15:15	1:15	Attend CSCI 529 class
4	Wednesday, September 18, 2019	22:30	23:59	1:29	Explore Data Visualization Tools/Datasets
4	Thursday, September 19, 2019	14:00	15:15	1:15	Attend CSCI 529 class
4	Friday, September 20, 2019	10:30	11:00	0:30	Meeting with Dr. Kinsman
4	Saturday, September 21, 2019	13:30	15:00	1:30	Explore Data Visualization Tools/Datasets
4	Sunday, September 22, 2019	13:00	15:10	2:10	Explore Data Visualization Tools/Datasets
5	Monday, September 23, 2019	20:30	23:10	2:40	Explore Data Visualization Tools/Datasets
5	Friday, September 27, 2019	8:30	11:00	2:30	Meeting with Dr. Kinsman
6	Tuesday, October 1, 2019	14:00	15:15	1:15	Attend CSCI 529 class
6	Wednesday, October 2, 2019	9:45	12:45	3:00	Dataset preparation
6	Thursday, October 3, 2019	14:00	15:15	1:15	Attend CSCI 529 class
6	Sunday, October 6, 2019	4:00	5:00	1:00	Understading Features in Dataset
7	Monday, October 7, 2019	10:00	11:00	1:00	Meeting with Dr. Kinsman
7	Tuesday, October 8, 2019	14:00	15:15	1:15	Presentation (We-Feel, Sentiment Viz)
7	Wednesday, October 9, 2019	9:45	12:45	3:00	Data Cleaning & Preprocessing
7	Thursday, October 10, 2019	14:00	15:15	1:15	Attend CSCI 529 class
7	Thursday, October 10, 2019	18:00	22:00	4:00	Data Cleaning & Preprocessing
7	Friday, October 11, 2019	10:30	11:00	0:30	Meeting with Dr. Kinsman
8	Monday, October 14, 2019	10:00	11:00	1:00	Data Cleaning & Preprocessing
8	Tuesday, October 15, 2019	14:00	15:15	1:15	Attend CSCI 529 class
8	Wednesday, October 16, 2019	9:45	12:45	3:00	Data Cleaning & Preprocessing
8	Thursday, October 17, 2019	14:00	15:15	1:15	Attend CSCI 529 class
8	Friday, October 18, 2019	10:30	11:00	0:30	Meeting with Dr. Kinsman
8	Saturday, October 19, 2019	10:00	12:00	2:00	Data Visualization using WordCloud
8	Sunday, October 20, 2019	14:00	15:15	1:15	Explore NLP + machine learning algorithms
9	Monday, October 21, 2019	9:45	12:45	3:00	Perform NLP operations

9	Tuesday, October 22, 2019	14:00	15:15	1:15	Attend CSCI 529 class
9	Wednesday, October 23, 2019	17:00	23:00	6:00	Learn Embedding Matrix concept and working
9	Thursday, October 24, 2019	14:00	15:15	1:15	Attend CSCI 529 class
9	Friday, October 25, 2019	10:30	11:00	0:30	Meeting with Dr. Kinsman
9	Friday, October 25, 2019	14:00	15:00	1:00	Learn Embedding Matrix concept and working
10	Tuesday, October 29, 2019	14:00	15:15	1:15	Attend CSCI 529 class
10	Thursday, October 31, 2019	14:00	15:15	1:15	Attend CSCI 529 class
10	Thursday, October 31, 2019	17:00	22:15	5:15	Learn RNN
10	Friday, November 1, 2019	10:30	11:00	0:30	Meeting with Dr. Kinsman
11	Wednesday, November 6, 2019	10:00	11:00	1:00	Learn LSTM
11	Thursday, November 7, 2019	14:00	15:15	1:15	Attend CSCI 529 class
11	Friday, November 8, 2019	14:00	15:00	1:00	Meeting with Dr. Kinsman
12	Monday, November 11, 2019	10:30	11:00	0:30	Learn working of LSTM +CNN
12	Tuesday, November 12, 2019	14:00	15:15	1:15	Attend CSCI 529 class
12	Wednesday, November 13, 2019	13:00	16:35	3:35	Learn working of LSTM +CNN
12	Friday, November 15, 2019	14:00	14:40	0:40	Meeting with Dr. Kinsman
12	Saturday, November 16, 2019	12:00	15:15	3:15	Model Training
13	Monday, November 18, 2019	10:30	12:00	1:30	Model Training
13	Tuesday, November 19, 2019	14:00	15:15	1:15	Attend CSCI 529 class
13	Wednesday, November 20, 2019	14:00	14:40	0:40	Model Training
13	Thursday, November 21, 2019	14:00	15:15	1:15	Attend CSCI 529 class
13	Friday, November 22, 2019	14:00	14:30	0:30	Meeting with Dr. Kinsman
13	Saturday, November 23, 2019	12:00	15:15	3:15	LSTM Model Evalutaion
13	Sunday, November 24, 2019	11:00	14:40	3:40	Visualize Model Prediction
14	Monday, November 25, 2019	10:30	13:40	3:10	Report Writing
14	Tuesday, November 26, 2019	14:00	15:15	1:15	Attend CSCI 529 class
14	Wednesday, November 27, 2019	10:30	13:40	3:10	Report Writing
14	Thursday, November 28, 2019	14:00	15:15	1:15	Attend CSCI 529 class
14	Friday, November 29, 2019	12:00	15:15	3:15	Report Writing
15	Monday, December 2, 2019	10:30	13:40	3:10	Report Writing
15	Tuesday, December 3, 2019	14:00	15:15	1:15	Attend CSCI 529 class
15	Wednesday, December 4, 2019	10:00	12:10	2:10	Meeting with Dr. Kinsman
15	Thursday, December 5, 2019	10:10	14:40	4:30	Revising the Report
15	Friday, December 6, 2019	14:00	15:00	1:00	Meeting with Dr. Kinsman
16	Monday, December 9, 2019	10:30	13:40	3:10	Revising the Report
16	Tuesday, December 10, 2019	16:00	18:15	1:15	Prepare Presentation for 529 class

16	Wednesday, December 11, 2019	14:00	15:00	1:00	Revising Presentation for 529 class Meeting with Dr. Kinsman
16	Thursday, December 12, 2019	11:10	16:40	5:30	Revising Presentation for 529 class Revising the Report
16	Friday, December 13, 2019	20:00	23:59	3:59	Revising the Report