A Multiclass Depression Detection in Social Media Based on Sentiment Analysis

Chapter · January 2020

DOI: 10.1007/978-3-030-43020-7_89

6 authors, including:

Raza Ul Mustafa
University of Campinas
27 PUBLICATIONS 153 CITATIONS

Fahad Shabbir Ahmed
Yale University
48 PUBLICATIONS 279 CITATIONS

Javed Ferzund
COMSATS University Islamabad
47 PUBLICATIONS 329 CITATIONS

Basit Shahzad
National University of Modern Languages
98 PUBLICATIONS 872 CITATIONS

A Multiclass Depression Detection in Social Media based on Sentiment Analysis

Raza Ul Mustafa[a], Noman Ashraf[b], Fahad Shabbir Ahmed[d], Javed Ferzund[a], Basit Shahzad[c], Alexander Gelbukh[b]

[a] *Department of Computer Science, COMSATS University Islamabad, Sahiwal Campus, Pakistan*
[b] *IPN - Computing Research Center - Mexico*
[c] *Deptartment of Software Engineering, National University of Modern Languages NUML, Pakistan*
[d] *Yale School of Medicine, New Haven, CT, USA*

Abstract

Depression is a common mental health disorder. Despite its high prevalence, the only way of diagnosing depression is through self-reporting. However, 70% of the patients would not consult doctors at early stage of depression. Meanwhile people increasingly relying on social media for sharing emotions, and daily life activities thus helpful for detecting their mental health. Inspired by these, we used the fourteen psychological attributes in Linguistic Inquiry and Word Count (LIWC) to classify these words into their respective classes of emotions. Moreover, weights were assigned to each word from happy to unhappy after classification by LIWC and trained a machine learning classifiers to classify the users into three classes of depression High,Medium, and Low. Total of 179 depressive individuals identified from dataset who have reported depression and they are on medical treatment. A sample of their recent tweets collected ranges from (200-3200) tweets per person. From these tweets, we gathered the 100 most frequently used words using Term Frequency-Inverse Document Frequency (TF-IDF). According to our study, better features selections and their combination will help to improve performance and accuracy of classifiers.

Keywords: `depression`, Twitter, social media,, machine learning, deep learning, anxiety

1. Introduction

The World Health Organization (WHO) predicts that by the year 2030 there will be 322 million people estimated to be suffer from depression [1]. Depression leads to mood disruption, uncertainty, loss of interest, tiredness, and physical issues [2]. Despite this, there is no laboratory test for diagnosing this type of illness. The subjects in this study identified their mental illness either by self-diagnosing or by being diagnosed by friends or family members. Symptoms expressed by a depress person are anxiety, restlessness, hopelessness, and misery, and these can frequently lead to thoughts of self-harm and suicide. People suffering from depression need continuous support from their family, friends, relatives and neighbors [3, 4, 5, 6].

With the development of Internet usage, many people have started sharing their personal feelings and mental illness on social platforms. Their activities on Social Media (SM) have encouraged many researchers to prevent this mental illness and detect its early stage before severe consequences. Many studies have identified these individuals from their proposed methods using Natural Language Processing (NLP) techniques. Research such as a bag of words (BOW), N-Grams, LDA and LWC have significant contributions in the literature [7, 8, 9]. They have used short messages collected from Twitter, Facebook and Reddit. Tyshchenko et al.[10] have worked on already proposed methods such as (LIWC + BOW + TFIDF) to increase performance using Convolutional Neural Network (CNN). Another exciting work have done by Calvo et al.[11]. They have used NLP and computational methods for the detection of mental illness. Even with recent significant progress in the field, the challenges are still there. This research aims to use a different methodology for the early detection of depressive individuals from Twitter. We considered diagnosed depressive users from Twitter for analysis and classified them into three classes (High, Medium, Low). We selected Twitter for its simplicity for the data collection on a certain topic. The most significant conversations are centered around a hashtag, which helps to detect people with similar interests. First, we considered a set of a dataset from twitter discussing depression on their tweets. We searched keywords related to depression on Twitter. Then manually selected 179 depressive users who have tweeted about their mental illness and they are on treatment. Later, we collected their recent tweets and extracted word frequency. Regarding the correlation, we focused on Linguistic Inquiry Word Count (LIWC) dictionary and classified collected word frequency into fourteen psychological attributes. Finally, we assigned weights to each word classified by LIWC based on a scale of happiness ranging from unhappy to happy (1-9) [12] a proposed method for the classification of depressive users into three classes High, Medium and Low. For classification we used Neural Network (NN), Support Vector Machine (SVM) [13], Random Forests (RF) and 1D Convolutional Neural Networks (1DCNN) [14]. A 1D CNN is very effective when you expect to derive interesting features from shorter (fixed-length) segments of the overall data set and where the location of the feature within the segment is not of high relevance. Suggested classification approach can be used to detect similar patterns on Twitter for timely handling severed consequences.

2. Contributions

Our study has main four main contributions.

- We have done document level classification, such as tweets of 179 users as 179 documents, and classified them into three classes of depression H, M, L.
- We propose approach for classification with a focus on identifying users suffering from depression based on their social words used in their tweets.
- We investigate and report the performance of several machine learning architectures commonly used in NLP tasks, in particular, to detect mental disorder.
- Finally, we have naturally annotated data that we have separated from normal users.

The rest of the paper is organized as follows. In section II, we discuss related work. In section III, we introduce the methodology and conduct data pre-processing followed by feature extraction. In section IV, we examine the results. We conclude our study and provide a direction for future work in section V.

3. Related Work

Depression is a severe public health challenge [15, 16, 17]. SM have been used for extracting psychological attributes from the text posted by its users. Billing and Moos [18] studied the role of stress in depression. The research provides strong evidence that SM environments contain a crucial source of information for dealing with depressive individuals. Choudhury et al. [19] used tweets to engage with the problem. They developed a statistical model that may be used by healthcare agencies for the detection of depressive users on SM before the illness progresses towards serious level. The attributes used in that study were user social activity, negative effects in tweets, highly clustered ego network, and evidence of suicidal thoughts in the text [20]. Robinson and Alloy [21] similarly observed that negative cognitive styles and stress reactive rumination were predictive of the onset, number, and duration of depressive episodes. Various other research studies have been conducted on the identification of depression on SM over the past few years [22]. These include the extraction of flu symptoms from the tweets and the building of a statistical classifier to check whether this contains any useful information relating to influenza [23]. Similarly, Moreno et al. [24] demonstrated that Facebook status updates could contain symptoms of major depressive episodes [25, 26]. On Twitter, users express their feelings and emotions; these short tweets can equally be used for the detection of depression [27]. Studies to date have improved the efficiency of the statistical model and conducted surveys on homogeneous samples of individuals [28, 7, 29, 30]; however, we have adopted a different methodology. We identified diagnosed depressive individuals from Twitter. Later, we divided the users into the High (H), Medium (M), and Low (L) classes of depression. We used the potential of

LIWC to detect emotions from text and classified the documents.

4. Methodology

4.1. Data Collection

We used the Twitter Developer Application Programming Interface (API) [31], for public data. We developed an application that fetches data using hashtags, query strings, and specific user data in python. We started collecting tweets in 2016 and continued until July 2019. We have 156511 tweets that contain 1989890 words. The keywords used for the desired dataset are listed in Table 1.

To apply NLP on a text, the data must be in a meaningful form. First, we converted the raw tweets into useful text. The first step in this approach is pre-processing. Pre-processing is a way of cleaning data. It involves data transformation, instance selection, normalization, and feature extraction. We removed unwanted text from the data, i.e., stops words, links, punctuation marks, and special characters. Thus, the representation of data in a high-quality format is the first and foremost step before running any analysis. Then we converted sentences into tokens a process called tokenization. Tokenization is the process of breaking a large string of data into smaller units that may include phrases and words often called tokens. These tokens are used to conduct quality analysis of the data. Of the two approaches to tokenization (phrase and word tokenization), word-level tokenization is considered more effective due to the resulting statistical significance [32, 33]. In this process, for instance, the sentence 'Previous depressions triggered by coming out bad relationship or even worse relationship' was separated into the tokens Previous, depressions, triggered, by, coming, out, bad, relationship, or, even, worse, relationship, etc. The algorithms used to tokenize a sentence separates the tokens based on the spaces between words and the built-in dictionary [12].

After tokenization, we assigned weights to the tokens based on their relative effectiveness. This process is known as feature weighting. A standard function

Table 1: Keywords used for the collection of depressed users data from Twitter.

diagnosed depression	mental illness	hopeless
feeling anxiety	depression	fuck
killing	suicide	die
ashamed	avoiding	doubting
afraid	hurting	missing

to compute the weights is TF-IDF [34]. The TF-IDF scheme is based on two parts: term frequency (TF) and inverse document frequency (IDF). TF is used to count the tokens represented in a document. It gives a complete count of term occurrences. One hundred most frequently used words using the TF-IDF collected from 179 users. The total number of words collected were 17,900. Later, we used LIWC which classified the words into fourteen psychological attributes. The categories selected from LIWC are listed in Table 2. Samples of words classified by LIWC of three different users listed in Table 3. In Table 3, ? indicates that depressed user 2 has not written any words belonging to the category Sexual.

Finally, we have assigned weights to each word classified by LIWC based on a scale of happiness ranging from unhappy to happy (1-9) for further categorical classification such as High, Medium and Low depression. Repetition of words were removed from the set of 17,900 words that makes 96 unique words for 179 users. After sorting the words in ascending order the categories based on weights are (1-3.9) = H, (4-6.9) = M, and (7-9) = L. Table 4, 5, and 6 show the words for the H, M, and L classes and their respective weights.

A *H* depressive user is more concerned in his/her interests, feeling worthless or guilty, difficulty with decision-making, and thoughts of suicide. These users have used words such as 'shit', 'panic', 'guilty', 'suicide', 'killing', 'dead', and 'anxiety'. Users with Premenstrual Dysphoric Disorder (PMDD) have symptoms of anxiety, fatigue, irritation, and mood swings. We have classified words of this class as *M*. The words most frequently used by this class of depressed

Table 2: Attributes selected from Linguistic Inquiry and Word Count

social	family	friends
religion	death	feel
health	sexual	risk
positive emotions	negative emotions	anxiety
anger	sad	

user are valentine, s*x, friends, soul, religion, and f**king. Some signs of fatigue, believing that someone is harming you, seasonal affective disorder (SAD), situational depression, and a typical depression were categorized as L. The words used by such users include bless, lover, heaven , and passion etc.

After assigning weights to 96 unique words of each user a string of (0,1) has made in such a way that each word of a single user is searched in a complete text of that user which is a collection of (200-3200) tweets. In case if the word found in the document, it is replaced by 1 otherwise 0 making a string of (0,1) of length 96 for each user. The algorithm 1 has used for such purpose.

Algorithm 1. Classifications of words into three classes of depression.

Input: sw = string words, iw = input words, sd = string document, ww = word weight, and A = matrix

Output: Depression class of the tweet in the form of H, M and L

1. For I $\leftarrow 0 \quad to \quad n$
2. do A[0,i] $\leftarrow swi \quad //all \quad the \quad 96 \quad words$
3. do A[1,i] $\leftarrow 0 \quad //initialize \quad all \quad with \quad zeros$
4. For i $\leftarrow 0 \quad to \quad n$
5. input iwi
6. If(iwi==xi)
7. Then A[1,i] $\leftarrow 1$
8. H $\leftarrow 0, M \leftarrow 0, L \leftarrow 0$
9. For j $\leftarrow 0 \quad to \quad n$
10. If ww[j] ≥ 1 and ww[j] ≤ 3.9

11. Then H $\leftarrow H+1$

12. Else if ww[j] = 4 to 6.9

13. Then M $\leftarrow M+1$

14. Else L $\leftarrow L+1$

15. If H >M and H >L

16. Then MaxVal $\leftarrow H$

17. Else if M >H and M >L

18. Then MaxVal $\leftarrow M$

19. Else MaxVal $\leftarrow L$

Where iw refers to input words, sd is used for the document string, which is usually a combination of 200 to 3200 tweets per user, ww is the weight assigned to each word, and A denotes the matrix. The function takes iw, sd, ww, and matrix A. The matrix contains two rows, the first is dedicated to unique string words and the second is reserved for the occurrence flag. In the first row, we have initialized 96 string words. The corresponding occurrence flag is initially set to 0. We classified words in such a way that each input word is searched for in each users tweet repository. The corresponding occurrence flag is set to 1 if the input word is located in each users tweet text. Finally, we made a document that has combinations of 0,1 for 179 distinct users. On line 8 of the above code, H, M, and L counters are initialized with value 0. The third loop, at line 9, contains a series of if statements to maintain the count of words that belong to each of the intensity levels, i.e., H, M or L. Thereafter, lines 15 to 19 are used to determine which intensity level has the highest count among the three. Here, the maximum value is the total number of words used by a depressed person from each of the H, M, and L classes.

We used Keras, a Python library for experiments that wraps the efficient numerical libraries Theano and TensorFlow. Theano is open-source numerical computational library, very valuable for fast numerical computations. We adopted the one-vs-all technique to differentiate the different level of depressed users. First High instances classified from Medium and Low, in the second step, Medium instances classified from High and Low, and finally Low separated from

Table 3: Samples of words from depressed users classified by LIWC into their respective categories

Attributes	**User 1**	**User 2**	**User 3**
positive emotions	good	good	good
negative emotions	hate	hurt	f**k
anxiety	scared	avoiding	afraid
anger	f**k	lying	f**k
sad	sorry	hurt	sorry
social	love	son	mom
family	baby	family	baby
friends	friend	guy	marriage
feel	hot	cool	feel
health	life	life	life
sexual	f**k	?	f**k
risk	protector	trust	safe
religion	monkeys	blessed	monkeys
death	murder	dying	die

High and Medium.

5. Results Discussion

A total of 179 diagnosed patients were extracted from the original dataset. The results of the proposed method are listed in Table 7. Three evaluation measures (precision, recall and f-measure) are used to evaluate the performance of classifiers. The mathematical definition of these measures with respect to a positive class is defined in equation 1,2,3 respectively.

$$Recall(R) = \frac{no \quad of \quad CPP}{no \quad of \quad PE} \tag{1}$$

$$Recall(R) = \frac{no \quad of \quad CPP}{no \quad of \quad PP} \tag{2}$$

Table 4: Keywords weights used to classify medium class of depression

Keywords	Weights	Keywords	Weights	Keywords	Weights
sh*t	3.91	clique	4.06	miss	4.1
ghost	4.23	porn	4.32	low	4.39
stop	4.73	queer	4.74	sorry	4.81
c**k	5.05	f**king	5.09	dwelling	5.21
f**k	5.23	bro	5.32	man	5.42
religion	5.42	people	5.7	hot	5.73
god	5.9	dude	5.91	king	6.0
ally	6.05	holy	6.06	gay	6.11
auntie	6.24	feel	6.27	valentine	6.4
smooth	6.42	guy	6.55	alive	6.57
soul	6.61	ready	6.64	baby	6.67
life	6.68	s*x	6.73	friend	6.79
cool	6.82	son	6.91		

Table 5: Keywords weights used to classify low class of depression

Keywords	Weights	Keywords	Weights	Keywords	Weights
bless	7.0	boyfriend	7.06	dad	7.14
date	7.18	mate	7.18	trust	7.24
family	7.25	protector	7.37	blessed	7.5
grandma	7.5	heaven	7.5	mother	7.53
passion	7.53	marriage	7.56	mom	7.64
safe	7.7	angel	7.71	good	7.89
live	7.95	love	8.0	lover	8.05
christmas	8.37				

$$F - measure = \frac{2 \quad * \quad P \quad * \quad R}{P \quad + \quad R} \tag{3}$$

In equations 1 and 2,CPP,PE and PP stand for correct positive predictions,

Table 6: Keywords weights used to classify high class of depression

Keywords	**Weights**	**Keywords**	**Weights**	**Keywords**	**Weights**
murder	1.48	sad	2.1	terrified	2.51
suicide	1.58	afraid	2.25	ashamed	2.52
die	1.67	depressed	2.27	lost	2.53
stress	1.79	fail	2.33	hell	2.55
kill	1.81	horrible	2.33	panic	2.56
death	1.89	anxiety	2.38	shame	2.62
hate	1.96	depression	2.44	fat	2.74
pain	2.0	hurt	2.45	scared	2.8
dead	2.02	upset	2.45	annoying	3.0
epidemic	2.05	mad	2.47	guilty	3.09
confused	3.11	cry	3.2	bad	3.24
unsure	3.37	lose	3.59	cut	3.9

positive examples and positive predictions respectively.

To further investigate the performance of the proposed method, another evaluation metric, i.e., Receiver Operating Characteristic (ROC) chart, is showed in Figure 1,2 and 3. The ROC chart is a plot of true positive rate (TPR) versus false positive rate (FPR) for various thresholds. An ROC chart with more area under the curve (AUC) is considered best.

6. Conclusion

In this study, we have extracted useful information from the tweets posted by diagnosed depressed individuals on Twitter. The identification and classification of word selections in the classes of H, M, and L depression constitute major findings. We identified the characteristics of symptoms for each of the three defined classes of depression, (H class) self-interest, feelings of worthlessness or guilt, problems with decision-making, suicidal thoughts. (M class) (including PMDD sufferers): mood swings, anxiety, fatigue, irritation.(L class) (including

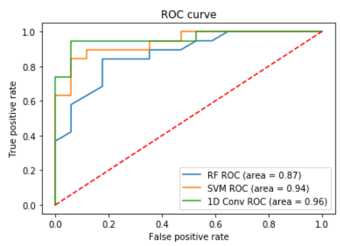

Figure 1: ROC Curve for (Low) vs (High and Medium) depressed users

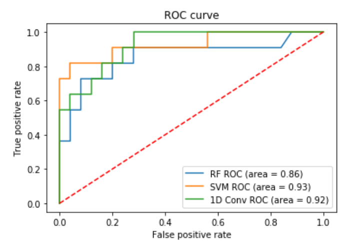

Figure 2: ROC Curve for (Medium) vs (Low and High) depressed users

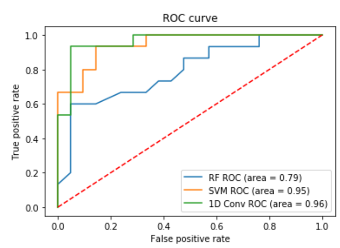

Figure 3: ROC Curve for (High) vs (Low and Medium) depressed users

Table 7: Overall, AUC, Precision, Recall and F-measure

Model	Comparison	AUC	Precision	Recall	F-measure
Conv1D	H (1), M,L (0)	0.91	0.92	0.86	0.89
Conv1D	M(1), H,L (0)	0.83	0.85	0.54	0.66
Conv1D	L(1), M,H (0)	0.86	0.93	0.78	0.85
NN	H (1), M,L (0)	0.89	0.78	0.78	0.78
NN	M (1), H,L (0)	0.89	0.83	0.83	0.83
NN	L (1), M,H (0)	0.88	0.83	0.83	0.83
SVM	H(1), M,L (0)	0.86	0.77	0.93	0.84
SVM	M (1), H,L (0)	0.91	0.90	0.81	0.85
SVM	L (1), M,H (0)	0.86	0.93	0.78	0.85
RF	H(1), M,L (0)	0.80	0.90	0.60	0.72
RF	M (1), H,L (0)	0.83	0.85	0.54	0.66
RF	L (1), M,H (0)	0.83	0.84	0.84	0.84

SAD sufferers and situational and atypical depression): some signs of fatigue or paranoia. We utilized the top 100 words used by depressive users to build a classifier that has classified users with an accuracy of 91%. In the future, we are interested in extracting further, more detailed information from depressive Twitter users, such as mood swings and changes in behavior with friends and family.

References

[1] C. J. Murray, A. D. Lopez, Alternative projections of mortality and disability by cause 1990–2020: Global burden of disease study, The Lancet 349 (9064) (1997) 1498–1504.

[2] N. W. Hur, H. C. Kim, L. Waite, Y. Youm, Is the relationship between depression and c reactive protein level moderated by social support in elderly?-korean social life, health, and aging project (kshap), Psychiatry investigation 15 (1) (2018) 24.

[3] A. Liu, B. Liu, D. Lee, M. Weissman, J. Posner, J. Cha, S. Yoo, Machine learning aided prediction of family history of depression, in: 2017 New York Scientific Data Summit (NYSDS), IEEE, 2017, pp. 1–4.

[4] A. Saha, M. Das, Impact of social networking sites on post-partum depression in women: An analysis in the context of bangladesh, in: 2017 20th International Conference of Computer and Information Technology (ICCIT), IEEE, 2017, pp. 1–6.

[5] A. Tiwari, R. Tiwari, Monitoring and detection of eeg signals before and after yoga during depression in human brain using matlab, in: 2017 International Conference on Computing Methodologies and Communication (ICCMC), IEEE, 2017, pp. 329–334.

[6] B. Liu, L. Zhang, A survey of opinion mining and sentiment analysis, in: Mining text data, Springer, 2012, pp. 415–463.

[7] M. M. Tadesse, H. Lin, B. Xu, L. Yang, Detection of depression-related posts in reddit social media forum, IEEE Access 7 (2019) 44883–44893.

[8] S. Paul, S. K. Jandhyala, T. Basu, Early detection of signs of anorexia and depression over social media using effective machine learning frameworks., in: CLEF (Working Notes), 2018.

[9] G. Coppersmith, M. Dredze, C. Harman, K. Hollingshead, From adhd to sad: Analyzing the language of mental health on twitter through self-reported diagnoses, in: Proceedings of the 2nd Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality, 2015, pp. 1–10.

[10] Y. Tyshchenko, depression and anxiety detection from blog posts data, Nature Precis. Sci., Inst. Comput. Sci., Univ. Tartu, Tartu, Estonia.

[11] R. A. Calvo, D. N. Milne, M. S. Hussain, H. Christensen, Natural language processing in mental health applications using non-clinical texts, Natural Language Engineering 23 (5) (2017) 649–685.

[12] G. Salton, C. Buckley, Term-weighting approaches in automatic text retrieval, Information processing & management 24 (5) (1988) 513–523.

[13] J. A. Suykens, J. Vandewalle, Least squares support vector machine classifiers, Neural processing letters 9 (3) (1999) 293–300.

[14] B. Hu, Z. Lu, H. Li, Q. Chen, Convolutional neural network architectures for matching natural language sentences, in: Advances in neural information processing systems, 2014, pp. 2042–2050.

[15] R. M. Khalil, A. Al-Jumaily, Machine learning based prediction of depression among type 2 diabetic patients, in: 2017 12th International Conference on Intelligent Systems and Knowledge Engineering (ISKE), IEEE, 2017, pp. 1–5.

[16] L. Yang, D. Jiang, W. Han, H. Sahli, Dcnn and dnn based multi-modal depression recognition, in: 2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII), IEEE, 2017, pp. 484–489.

[17] A. G. Billings, R. H. Moos, Coping, stress, and social resources among adults with unipolar depression., Journal of personality and social psychology 46 (4) (1984) 877.

[18] M. De Choudhury, M. Gamon, S. Counts, E. Horvitz, Predicting depression via social media, in: Seventh international AAAI conference on weblogs and social media, 2013.

[19] E. C. Tandoc Jr, P. Ferrucci, M. Duffy, Facebook use, envy, and depression among college students: Is facebooking depressing?, Computers in Human Behavior 43 (2015) 139–146.

[20] M. S. Robinson, L. B. Alloy, Negative cognitive styles and stress-reactive rumination interact to predict depression: A prospective study, Cognitive Therapy and Research 27 (3) (2003) 275–291.

[21] S.-K. Chen, S. S. Lin, A latent growth curve analysis of initial depression level and changing rate as predictors of problematic internet use among college students, Computers in Human Behavior 54 (2016) 380–387.

[22] M. I. U. Lali, R. U. Mustafa, K. Saleem, M. S. Nawaz, T. Zia, B. Shahzad, Finding healthcare issues with search engine queries and social network data, International Journal on Semantic Web and Information Systems (IJSWIS) 13 (1) (2017) 48–62.

[23] M. A. Moreno, L. A. Jelenchick, K. G. Egan, E. Cox, H. Young, K. E. Gannon, T. Becker, Feeling bad on facebook: Depression disclosures by college students on a social networking site, Depression and anxiety 28 (6) (2011) 447–455.

[24] B. A. Primack, A. Shensa, C. G. Escobar-Viera, E. L. Barrett, J. E. Sidani, J. B. Colditz, A. E. James, Use of multiple social media platforms and symptoms of depression and anxiety: A nationally-representative study among us young adults, Computers in human behavior 69 (2017) 1–9.

[25] M. Park, C. Cha, M. Cha, Depressive moods of users portrayed in twitter, in: Proceedings of the ACM SIGKDD Workshop on healthcare informatics (HI-KDD), Vol. 2012, 2012, pp. 1–8.

[26] K. Makice, Twitter API: Up and running: Learn how to build applications with the Twitter API, " O'Reilly Media, Inc.", 2009.

[27] J. Dieris-Hirche, L. Bottel, M. Bielefeld, T. Steinbuechel, A. Kehyayan, B. Dieris, B. te Wildt, Media use and internet addiction in adult depression: A case-control study, Computers in Human Behavior 68 (2017) 96–103.

[28] M. Deshpande, V. Rao, Depression detection using emotion artificial intelligence, in: 2017 International Conference on Intelligent Sustainable Systems (ICISS), IEEE, 2017, pp. 858–862.

[29] J. H. Seah, K. J. Shim, Data mining approach to the detection of suicide in social media: A case study of singapore, in: 2018 IEEE International Conference on Big Data (Big Data), IEEE, 2018, pp. 5442–5444.

[30] Q. Cong, Z. Feng, F. Li, Y. Xiang, G. Rao, C. Tao, Xa-bilstm: a deep learning approach for depression detection in imbalanced data, in: 2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), IEEE, 2018, pp. 1624–1627.

[31] Twitter Developer Aplication Programming API , `https://developer.twitter.com/`, [Online; accessed 1-July-2016].

[32] F. Sebastiani, Machine learning in automated text categorization, ACM computing surveys (CSUR) 34 (1) (2002) 1–47.

[33] A. B. Warriner, V. Kuperman, M. Brysbaert, Norms of valence, arousal, and dominance for 13,915 english lemmas, Behavior research methods 45 (4) (2013) 1191–1207.

[34] M. S. Nawaz, R. U. Mustafa, M. I. U. Lali, Role of online data from search engine and social media in healthcare informatics, in: Applying Big Data Analytics in Bioinformatics and Medicine, IGI Global, 2018, pp. 272–293.