Healthcare Transformation with Informatics and Artificial Intelligence
J. Mantas et al. (Eds.)

doi:10.3233/SHTI230520

Automatic Profiles Collection from Twitter Users with Depressive Symptoms

Akkapon Wongkoblap[a,1]
[a] *Institute of Digital Arts and Science, Suranaree University of Technology, Thailand*
ORCiD ID: Akkapon Wongkoblap https://orcid.org/0000-0002-9355-1981

Abstract. Mental illness is a pressing issue that needs urgent attention, as the number of people suffering from mental disorders continues to increase. Diagnosing mental health disorders can be challenging, and gathering information about a patient's medical history and symptoms is crucial for an accurate diagnosis. Self-disclosure on social media can provide valuable insights into whether users may be suffering from a mental illness. This paper proposes a method for automatically collecting data from social media users who disclosed their depression. The proposed approach yielded a 97% accuracy rate with a majority of 95%.

Keywords. Machine learning, Depression, Social media, Data collection

1. Introduction

Mental illnesses are a pressing issue that needs to be addressed urgently, as the number of people suffering from mental disorders continues to increase. According to a report by the World Health Organization (WHO), an estimated 280 million people are experiencing mental health issues [1]. Mental illnesses are also a major cause of life problems. These disorders are difficult to diagnose and prevent.

The diagnosis of mental health disorders can be challenging. Gathering information about the patient's medical history and symptoms is crucial for an accurate diagnosis. Medical professionals who diagnose mental illness must often rely on information provided by the patient or those close to them [2]. However, this can be difficult as patients may have difficulty recalling information about their symptoms or history over the past few weeks or even months.

Mental health self-disclosure by users on social media platforms can provide insight into whether users may be suffering from a mental illness [3,4. This information is publicly available online.

The main purpose of this paper is to propose a method for automatically collecting data from social media users who have depression. This method does not require human assistance or manual data annotation.

[1] Corresponding Author: Akkapon Wongkoblap, Institute of Digital Arts and Science, Suranaree University of Technology, Thailand. Email: wongkoblap@sut.ac.th.

2. Related work

This work focuses on text analysis and an automatic approach for collecting social media users who exhibit symptoms of depression. Relevant publications in this area are reviewed below.

Collecting data from users who exhibit symptoms of depression is a crucial and challenging task. Various methods are used to collect this data, including asking participants to screen their depressive symptoms using questionnaires [5,6]. Self-disclosure is a common approach, where users openly state that they suffer from depression [3].

Textual content analysis tools have been developed and advanced to better understand the content of generated text. These tools help researchers explore insightful information behind self-disclosure in mental health, and machine learning models can potentially detect social media users with depression [7].

The use of hashtags has become widespread as a means of representing short meanings of generated textual content. They have proven to be useful in various areas, including tracing users' interests and capturing trending topics [8]. The co-occurrence of hashtags can provide semantically related information about a tweet. Word embedding techniques can also capture correlated topics [9].

3. Methods

A search was conducted for public tweets containing the hashtag "#depression" within a 10-week window between October 1st and December 9th, 2022. This search yielded 4,673 tweets from 2,668 unique users. The dataset was then refined by removing tweets with a number of hashtags greater than the average, resulting in a final dataset of 1,676 tweets from 1,289 unique users after further exclusion of tweets that were replies to other users.

Of these 1,676 tweets, 1,842 hashtags were identified. Any hashtags used by only one user were removed, leaving 72 hashtags from 395 unique users. A word embedding model was built using Word2Vec from Gensim [10], using all included hashtags. The dimensions of Word2Vec were 300.

After building the word embedding model, we extracted 10 hashtags related to depression from the model. These hashtags are mentalhealthmatters, sad, depressed, bipolardisorder, bipolar, mentalhealthawareness, mentalhealth, sadness, seasonalaffectivedisorder, and mentalillness. Users who only tweeted these hashtags were included in our dataset, resulting in 73 user profiles.

Next, we randomly searched for tweets publicly posted between December 1st and December 7th, 2022, and set the number of tweets collected per day to 260. This resulted in a total of 1,820 tweets from 1,360 unique users, because some users published many tweets during the time window. We then collected tweets on the profiles of 1,360 users who did not self-disclose depression.

4. Results

After collecting tweets from the 1,433 users with and without self-disclosure of depression, we obtained a dataset of 3.3 million and 140,000 tweets, respectively. Twitter

APIs allow the collection of tweets up to 3,200 tweets per a user. We used several machine learning techniques to train a predictive model for classifying users based on their social media profiles as having or not having self-disclosure of depression. Before evaluating our models, we split the dataset into 70% of the training set and 30% of the test set. The best classifier was trained using the AdaBoostClassifier with CountVectorizer feature extraction from scikit-learn, a Python library for building machine learning models (11). To test models, the best model achieved an accuracy of 97%, and its weighted precision, recall, and F1-score were 0.97, as shown in Table 1. As can been seen in Figure 1, the model achieved the areas under the curve 96%. It is worth noting that the majority class from our dataset was 95%.

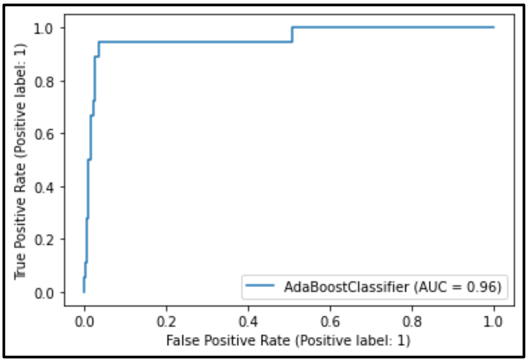

Figure 1. Receiver operating characteristic curves of the model trained using the AdaBoostClassifier with CountVectorizer

Table 1. The precision, recall, and F1-score of the model trained using the AdaBoostClassifier with CountVectorizer

Class	Precision	Recall	F1-score
Non-depression	0.98	0.99	0.98
Depression	0.62	0.56	0.59
Weighted average	0.97	0.97	0.97

5. Conclusion

The main goal of this study is to investigate the automatic data collection from users with self-disclosure of depression by using hashtags. The experiment above can be seen that the word embedding model can be used to find relevant topics to depression. The use of hashtags related to depression topics provided by our model can truly retrieve users with self-disclosure of mental health issues. After collecting social media users as having or not having self-disclosure of depression, a set of predictive models were trained and yielded the best accuracy of 97%.

The experiment shows promising results, however there is also room for improvement. This research used default parameters. Tuning parameters may improve a result of models. There is a small amount of data in this dataset. In our future work, we are collecting more data and verifying each tweet contains a genuine statement of mental health self-disclosure. This will assure that our proposed models can collect tweets related to mental health self-disclosure efficiently and reliably.

References

[1] World Health Organization. Depression [Internet]. 2021 [cited 2023 Mar 24]. Available from: https://www.who.int/news-room/fact-sheets/detail/depression.

[2] Perkins A, Ridler J, Browes D, Peryer G, Notley C, Hackmann C. Experiencing mental health diagnosis: a systematic review of service user, clinician, and carer perspectives across clinical settings. The Lancet Psychiatry [Internet]. 2018 Sep;5(9):747–64. Available from: https://linkinghub.elsevier.com/retrieve/pii/S2215036618300956.

[3] Coppersmith G, Dredze M, Harman C. Quantifying Mental Health Signals in Twitter. In: Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality [Internet]. Stroudsburg, PA, USA: Association for Computational Linguistics; 2014. p. 51–60. Available from: http://www.aclweb.org/anthology/W/W14/W14-3207.

[4] Wongkoblap A, Vadillo MA, Curcin V. Deep Learning With Anaphora Resolution for the Detection of Tweeters With Depression: Algorithm Development and Validation Study. JMIR Ment Heal [Internet]. 2021 Aug 6;8(8):e19824. Available from: https://mental.jmir.org/2021/8/e19824.

[5] De Choudhury M, Gamon M. Predicting Depression via Social Media. Proc Seventh Int AAAI Conf Weblogs Soc Media [Internet]. 2013;2:128–37. Available from: http://www.aaai.org/ocs/index.php/ICWSM/ICWSM13/paper/viewFile/6124/6351.

[6] Chancellor S, De Choudhury M. Methods in predictive techniques for mental health status on social media: a critical review. npj Digit Med [Internet]. 2020 Mar 24;3(1):43. Available from: https://www.nature.com/articles/s41746-020-0233-7.

[7] Wongkoblap A, Vadillo MA, Curcin V. Researching Mental Health Disorders in the Era of Social Media: Systematic Review. J Med Internet Res [Internet]. 2017 Jun 29;19(6):e228. Available from: http://www.ncbi.nlm.nih.gov/pubmed/28663166.

[8] Kumar N, Baskaran E, Konjengbam A, Singh M. Hashtag recommendation for short social media texts using word-embeddings and external knowledge. Knowl Inf Syst [Internet]. 2021 Jan 14;63(1):175–98. Available from: https://link.springer.com/10.1007/s10115-020-01515-7.

[9] Wang B, Wang A, Chen F, Wang Y, Kuo C-CJ. Evaluating word embedding models: methods and experimental results. APSIPA Trans Signal Inf Process [Internet]. 2019;8(1). Available from: http://www.nowpublishers.com/article/Details/SIP-124.

[10] \v Reh\r u\v rek R, Sojka P. Software Framework for Topic Modelling with Large Corpora. In: Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks. Valletta, Malta: ELRA; 2010. p. 45–50.

[11] Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, et al. Scikit-learn: Machine Learning in {P}ython. J Mach Learn Res. 2011;12:2825–30.