

A Time Series Analysis on Depression During the COVID-19 Period

Alejo Vallega^{#1}, Devin Efendy^{#2}, Kevin Kim^{#3}, Victor Sharonov^{#4}, Joseph Smith^{#5}

[#]*Department of Computer Science, University of Manitoba
66 Chancellors Cir, Canada*

¹vallegaa@myumanitoba.ca

²smithj32@myumanitoba.ca

³efendyd@myumanitoba.ca

⁴kimh3427@myumanitoba.ca

⁵sharonov@myumanitoba.ca

Abstract— This document gives formatting instructions for authors preparing papers for publication in the Proceedings of an IEEE conference. The authors must follow the instructions given in the document for the papers to be published. You can use this document as both an instruction set and as a template into which you can type your own text.

Keywords— COVID-19, Depression, Machine Learning Classifiers, Twitter

I. INTRODUCTION

The novel coronavirus disease (COVID-19) has been declared as a pandemic by the World Health Organization (WHO) on March 11, 2020. It is disheartening that, as of December 2020, around 67 million confirmed cases of COVID-19, including 1.5 million deaths, are reported to WHO [1]. This COVID-19 has continued to be prevalent even in the end of 2020, significantly affecting the people's lifestyle and their physical and mental well-being [2].

Depression is one of the common mental disorders found from people during the COVID-19 period. It is a leading cause of disability worldwide and a major contributor to the overall global burden of disease [1]. Traditionally, depression is often diagnosed by a psychological doctor interviewing a patient face-to-face via referring to clinical depression criteria. However, in general, people are somehow ashamed to talk to a psychological doctor or unaware of depression, which leads to more than 70% of people in the early stages of depression would not consult doctors, letting depression deteriorate their conditions [3].

Instead of seeking professional assistance, people are increasingly relying on social media platforms,

such as Facebook and Twitter, to express their emotions as well as their personal statuses.

During our time that we spent on social media, we observed that was a sign of increased depressive symptoms within our social media feed (Twitter). This observation ...

This study exploits data collected from (how many?) user profiles and around 100,000 tweets. Several machine learning classifier techniques are utilized to identify the depression level, which include support vector machines (SVM), Naive Bayes (NB) and Random Forest (RF).

This paper aims to see if there exist new keywords or features from the depressions related tweets during the COVID-19 period and compare them to existing keywords and features that indicate depression of users.

Our key contribution of this paper is a time series of tweets related to depression during the covid-19 period. Specifically, providing a visualization of the number of depressions related tweets on Twitter during the particular COVID-19 period (April to September). The tweets that indicate depression are classified by our Machine Learning model that we trained. In addition to that, after completing classification on tweets using our machine learning models, we are doing feature extraction on the tweets that are classified as depressed during the COVID-19 period.

The rest of the paper is organized as follows: Section II provides background and related works on depression detection. Section III presents which

datasets are used and how datasets are preprocessed prior to applying the machine learning algorithm. Section IV and V describe what features are extracted and which machine learning algorithms are used to detect depression from the datasets. Section VI provides time series analysis (Need more details here). Then, we conclude our study and provide a direction for future work in section VII.

II. BACKGROUND AND RELATED WORK

Efforts to analyze depression of an individual have existed much earlier than the appearance of the Internet. There are many widely-accepted scales and criteria have been developed based upon the user study or questionnaire survey. In the areas of medicine and psychology, several questionnaire-based measures for rating depression in individuals have been proposed [4, 5, 6, 7]. For instance, Center for Epidemiological Studies-Depression (CES-D), Beck's Depression Scale (BDI) and Zung's Self-rating Depression Scale (SDS) estimate the severity of depression in individuals from the self-reported answers to 20 questions [4, 6, 8]. The questions either have several options aligned with different scores or require participants to evaluate the severity of their circumstances. Then, the level of depression is determined according to the scale of the total score [9]. In general, however, obtaining data through a survey or questionnaire is often expensive and sometimes time-consuming.

Nowadays, it is commonly seen that almost everyone has an active account in at least one social media, such as Facebook and Twitter, allowing a large scale of data to be generated in a short period of time. For example, Facebook has about 2.7 billion active users and 350 million posts are uploaded in a single day [Footer 1]. Twitter owns around 340 million active users and 500 million tweets (user's posts in Twitter) are generated in a single day, as of December 2020 [Footer 2]. Through the use of social media's own API, such as Graph API Explorer (for Facebook) and Twitter Search API, researchers can easily access and obtain large scale data of the users. As the large scale data is available publicly due to the presence of social media, approaches that use such data for

depression analysis are seen to be compelling to researchers and thereby providing motivation to analyze the online behaviors of depressed users.

(Tendency to post about their emotion to social media)

Moreno et al. propose that college students experiencing depressive mood show symptoms consistent with depression on Facebook and place greater investment in social media as a communication outlet because it could be viewed as a safe and indirect outlet for their emotions [10].

(Analyze depressed and non-depressed users)

Park et al. explored the use of language in describing depressive moods by utilizing real time moods captured from Twitter users and analyzed the differences between Twitter users with and without depression by analyzing their activities [11]. In their later work, a similar analysis is done by analyzing data from Facebook [12].

(Accuracy of prediction using SVM)

De Choudhury et al. demonstrate the estimation accuracy that could be achieved by utilizing activities on Twitter to predict depression of the users [13]. They obtained training data for machine learning by crowdsourcing (the practice of engaging a crowd or group for a common goal). Then, models that could be used to predict risk of depression were identified from several features obtained from the records of user activity on Twitter tweets by using Support Vector Machine (SVM). The result of their experiments show that depression can be recognized among Twitter users with an average accuracy of 70% [13]. These approaches are also applied to predict mothers' postpartum depression (the depression after giving birth) from Facebook and Twitter as well [13, 14].

(Bag of Word and feature extraction)

Tsugawa et al. showed that the word frequencies are useful for identifying depression and investigated how useful the various features extracted from Twitter user history are for recognizing depression, and the degree of accuracy with which the presence of active depression could be detected by using these features [7, 16].

(Bag of Word, SVM, DT and NB. Found that NB performed better than other classifiers)

Nadeem et al. employed a Bag of Words (BOW) approach which utilizes word occurrence

frequencies to quantify the content of a tweet (i.e. putting all words within a bag and measuring how commonly each word appeared). used four types of binary classifiers: linear SVM classifier, decision tree (DT), Naïve Bayes (NB) algorithm, and logistic regression. They found that NB algorithm produced an accuracy of 81% and precision of 0.86, achieving better performance than the other classifiers [15].

Write how **our work** is going to be different than the aforementioned works.

Background and related work (Kevin will write stuffs of the followings, though I think these can go under feature extraction section?):

- Define terms here.
- pre-processing techniques
- feature extraction (tf-idf, bag of words)
- SVM, Naive Bayes (multinomial model in python), and Random Forest
- Talk about results. Evaluation metrics
- What classifies depression
- sample code?

III. DATA COLLECTION

For this research, what and how datasets are collected?

In this study, we collected data from [IEEE Covid-19 datasets***](#).

Any particular information to highlight which criteria we used to collect data?

Talk about:

- [swcwang/depression-detection](#) dataset and how the tweets related to depression are manually picked.
- Also, how we used this dataset for machine learning purposes.
- This dataset did not meet the best accuracy due to lack of samples so we used other multiple datasets but were only extracted using depression hashtag. Which of course lacks reliability.
- [IEEE Covid-19 datasets***](#) that we used to create the time series analysis

Talk about why we want to exclude/include specific stopwords given how depressed users tend to use more first person pronouns .

IV. FEATURE EXTRACTION

Do feature feature-extraction on the training dataset to remove words that we think are not contributing to the classification of depression.

Show keywords extracted using various algorithms.

V. MACHINE LEARNING ALGORITHM

Talk about which machine learning algorithms are used (SVM, NB, RF).

SVM

NB

RF

Elaborate why an algorithm performed better than the other.

Talk about the metric results for each algorithm

Elaborate on parameter tuning for accuracy improvement

VI. TIME SERIES ANALYSIS

What new keywords or features from the depressions related tweets during the COVID-19 period are found? Not enough information to talk about yet

Any particular differences (or interesting aspects) compared to existing keywords and features that indicate depression of users?

VII. CONCLUSION

In this study, what have tried to do with the datasets we collected?

Limitation

Future work

REFERENCES

- [1] W. H. Organization. (2017). Depression and Other Common Mental Disorders: Global Health Estimates. Geneva: World Health Organization. [Online]. Available: <http://www.who.int/en/newsroom/fact-sheets/detail/depression>
- [2] Bueno-Notivol, Juan et al. "Prevalence of depression during the COVID-19 outbreak: A meta-analysis of community-based studies." *International journal of clinical and health psychology : IJCHP*, 100196. 31 Aug. 2020, doi:10.1016/j.ijchp.2020.07.007
- [3] Shen, G., Jia, J., Nie, L., Feng, F., Zhang, C., Hu, T., Chua, T.-S., & Zhu, W. Depression detection via harvesting social media: A multimodal dictionary learning solution in IJCAI 3838-3844 (2017).
- [4] Beck, A. T., Ward, C. H., Mendelson, M., Mock, J., and Erbaugh, J. An inventory for measuring depression. *Archives of General Psychiatry* 4, 6 (June 1961), 561–571.
- [5] Hamilton, M. Development of a rating scale for primary depressive illness. *British Journal of Social & Clinical Psychology* 6, 4 (Dec. 1967), 278–296.
- [6] Radloff, L. S. The CES-D scale a self-report depression scale for research in the general population. *Applied Psychological Measurement* 1, 3 (1977), 385–401.
- [7] Tsugawa, Kikuchi. "Recognizing Depression from Twitter Activity." *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, ACM, 2015, pp. 3187–96, doi:10.1145/2702123.2702280.
- [8] Zhung, W. W. K. A self-rating depression scale. *Archives of General Psychiatry* 12, 1 (1965), 63–70.
- [9] Shen, Guangyao, et al. "Depression Detection via Harvesting Social Media: A Multimodal Dictionary Learning Solution." *IJCAI*. 2017.
- [10] Moreno, Jelenchick. "Feeling Bad on Facebook: Depression Disclosures by College Students on a Social Networking Site." *Depression and Anxiety*, vol. 28, no. 6, Wiley, June 2011, pp. 447–55, doi:10.1002/da.20805.
- [11] Park, M., Cha, C., and Cha, M. Depressive moods of users portrayed in twitter. In *Proceedings of the ACM SIGKDD Workshop on Healthcare Informatics (HI-KDD'12)* (Aug. 2012), 1–8.
- [12] Park, S., Lee, S. W., Kwak, J., Cha, M., and Jeong, B. Activities on Facebook reveal the depressive state of users. *Journal of Medical Internet Research* 15, 10 (Oct. 2013), e217.
- [13] De Choudhury, M., Gamon, M., Counts, S., and Horvitz, E. Predicting depression via social media. In *Proceedings of the 7th International AAAI Conference on Weblogs and Social Media (ICWSM'13)* (July 2013), 128–137.
- [14] De Choudhury, M., Counts, S., and Horvitz, E. Predicting postpartum changes in emotion and behavior via social media. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI'13)* (Apr. 2013), 3267–3276.
- [15] Nadeem, Moin. Identifying Depression on Twitter. July 2016.
- [16] Tsugawa, S., Mogi, Y., Kikuchi, Y., Kishino, F., Fujita, K., Itoh, Y., and Ohsaki, H. On estimating depressive tendency of twitter users from their tweet data. In *Proceedings of the 2nd International Workshop on Ambient Information Technologies (AMBIT'12)* (Mar. 2013), 29–32.
- [17] Write Reference Here
- [18] Write Reference Here
- [19] Write Reference Here
- [20] Write Reference Here
- [21] Write Reference Here
- [22] Write Reference Here
- [23] Write Reference Here
- [24] Write Reference Here
- [25] Write Reference Here

Footer (Kevin -> I tried to add footer only in the page needed, but it appears to be added on all of the pages. So I have created a separate footer section in case if you are referencing something from websites)

- 1) <https://www.omnicoreagency.com/facebook-statistics/#:~:text=350%20million%20photos%20are%20uploaded,300%2C000%20users%20helping%20in%20translation>.
- 2) <https://www.omnicoreagency.com/twitter-statistics/>