

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 for depression detection. Section III presents which

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

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.

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]. 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].

De Choudhury's work

(Predicting postpartum changes in emotion and behavior via social media. and Characterizing and predicting postpartum depression from shared facebook data.)

Tsugawa et al.

(Tsugawa, S., Kikuchi, Y., Kishino, F., Nakajima, K., Itoh, Y., and Ohsaki, H. Recognizing depression from twitter activity in Recognizing depression from twitter activity 3187-3196 (ACM, 2015).)

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

III. DATA COLLECTION

For this research, what and how datasets are collected?

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

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- 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/>