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

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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

Explain the methodology of depression analysis prior to the existence of the Internet (i.e. how did the researchers know if a person is depressed in old times?)

Efforts to analyze depression of a person have existed much before 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 users 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 costly and sometimes very time-consuming.

Explain amount of data generated by social media (mainly Facebook and Twitter)

Nowadays, it is commonly seen that almost everyone has an account in at least one social media, such as Facebook and Twitter, allowing the availability of large scale data to be generated in a short period of time. For example, Twitter owns around 340 million active users and 500 million tweets (posts) are generated in a single day, as of December 2020 [Footer 1]. As the large-scale data

is available publicly (through use of Twitter Search API in our case) due to such social media, approaches that use such data for depression screening are receiving increased attention from researchers and thereby started to analyze the online behaviors of depressed users.

De Choudhury's work (will be added later)

Related works (what researchers have done regarding depression analysis and any particular drawbacks (shortcoming) you want to highlight?)

Background and related work (Kevin will write stuffs of the followings):
- 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

Related Work:
- Find other papers that do this similar stuff. Point out shortcoming (i.e. disadvantages, drawbacks of an approach)
- Depression detection in social media
- Prevalence of depression symptoms before and during the covid period

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

IV. Data pre-processing

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

V. 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.

VI. 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

VII. Time Series Analysis

Not enough information to talk about yet

What new keywords or features from the depressions related tweets during the COVID-19 period are found?

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

VIII. Conclusion

Not enough information to talk about yet

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

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