A literature review of Mental Health prediction during different stages of Covid-19

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1 INTRODUCTION

The global pandemic has disrupted the daily life of millions. The COVID-19 virus has affected people both mentally and physically. To protect themselves and their community from the virus, people have had to give up a little bit of freedom, which has impacted people's mental health. During these times, many found comfort in sharing their feelings and emotions through different social media. Even though the pandemic is not over, we have been through many different stages, including lockdowns, mask mandates, school closing, and vaccination rollout. So I will be predicting people's sentiments during various stages of the pandemic through Twitter Sentiment Analysis. I will be using an open-source repository of COVID-19 related tweets to create my data set [1]. This repository contains multilingual COVID-19 corresponding tweets IDs, which I will use to extract the contents from twitter's API. I will then filter out all the retweets and non-English tweets. Then to measure the emotional valence of tweets, I will use Valence Aware Dictionary and Sentiment Reasoner (VADER). I will be predicting whether people's sentiments change during different periods of the pandemic. I might use PELT (Pruned Exact Linear Time) algorithm to find significant changes in people's sentiments and check whether the change is related to a new COVID-19 update, a new COVID-19 related regulation, or discovery of COVID-19 vaccine.

2 TWITTER

Twitter has a huge following all over the world. It has a total number of 330 million daily active users [3]. These users share their feelings and views on various topics, vital information for companies and organizations that benefit from learning people's preferences and beliefs. To analyze the publics' opinions and preferences on these topics, we do Sentiment analysis on the tweets. Many Researchers have used Twitter to predict the sentiments of people during the COVID-19 pandemic. Xue et al. used Twitter dataset to identify latent topics related to COVID-19, the themes of the identified topics, how Twitter users are reacting to the pandemic emotionally, and how their sentiments are changing over time [8]. Doogan et al. also used Twitter dataset, with 777,869 English language tweets about COVID-19 in six countries, and analyzed these to find the public perception towards Nonpharmaceutical interventions (NPIs) (wearing masks and social distancing) [2].

2.1 Data collection

Manguri et al. used Python's Tweepy library to extract data using Twitter's API and then removed all the retweets to avoid duplication [5]. They fetched tweets with the keywords COVID-19 and CORONAVIRUS and stored it in a CSV file. Their target information was the timestamp and the contents of the tweet. They extracted the tweets in the week of 09-04-2020 to 15-04-2020, with no restriction on a particular continent, country or city. The number of tweets they fetched during this week was 500,000 tweets.

Valdez et al used an open-source repository of COVID-19 related tweets IDs created by Chen et al. [1] [7]. The repository contains a collection of multi-lingual COVID-19 related tweets IDs since January 28, 2020. Veldez et al. used these tweets IDs to extract the contents from Twitter's API [7]. They named this data set "COVID-19 corpus." Then they created another data set, called User timeline data, which contained the individual user's Twitter timelines (3200 most recent tweets), and the tweets did not have to be related to COVID-19. They used this dataset to measure the fluctuations in mood, behavior, and emotions of individual users included in the COVID-19 corpus and living in the 20 US cities with the most COVID-19 cases per 100,000 people. They also removed non- English tweets, retweets, and keywords like "coronavirus," "Covid-19", "pandemic", from User timeline data, to make sure they measured the sentiments of people without any biases. They removed the above-stated keywords because they believed that these words inherently have negative connotations, decreasing sentiment and not accurately reflect people's well-being.

Dubey collected COVID-19 related tweets from twelve countries to identify the emotions people were sharing around the world. He used RTweet package in R to collect 50,000 tweets with the keywords COVID19, CORONAVIRUS, CORONA, STAY HOME STAY SAFE, and COVID19Pandemic. To avoid duplication, he filtered out retweets and replies. Then he cleaned up the data by removing white spaces, stop words, links, and punctuation and converted the tweets to lower case.

3 TWITTER SENTIMENT ANALYSIS

3.1 Classic Dictionary Style

According to Nemes et al., in the classical dictionary style, there is a pre-set vocabulary where each word's effect is given a value, which is either positive or negative [6].To do the sentiment analysis of a sentence, the sentence is first broken down. Each word is identified, then using the dictionary values, the given value is assigned to the effect of the word, and the sum of these values is the sentiment of that particular sentence. However, this way of sentiment analysis is not ideal. There are ways where the prediction can be inaccurate. For example, there could be word combinations that could change the emotions which may not be detected. Therefore, modern sentiment analysis usually uses deep learning.

3.2 Deep learning - RNN

Nemes et al. built an RNN model (Recurrent Neural Network) using tools provided by Tensorflow and Keras [6]. A neural network is run multiple times, and whatever it learns the first time is fed as input in the second run, and what it learns in the second run is fed into the third run. Like this, the RNN model slowly trains and predicts the sentiments of the entire sequence. Their RNN model searched for connections between words and marked them with a class of emotional strengths, weakly positive, weakly negative, strongly positive, strongly negative. When fed with coronavirus-related tweets, the model showed that the overall sentiments were positive, although negative and other sentiments were also present. They also compared the results they got using RNN with the results using TextBlob; they did this for different periods. Although RNN model results and Textblob results both showed a positive manifestation overall, the RNN model did a better job making a decision and placing the sentiment in a category. RNN model results had either a very small amount or zero amount of data classified as neutral. In contrast, while using the Textblob function, there were many times when the neutral results were above 30 percent. Overall the RNN model was able to provide a more detailed sentiment level result.

3.3 VADER

Valdez et al. used Valence Aware Dictionary and Sentiment Reasoner (VADER) to find out the valence of tweets [4] [7]. VADER considers grammatical structures like punctuation, negation, hedging, and magnification while also recognizing common terms, idioms, abbreviations, and jargon. The 7500 + terms that it contains are rated for their emotional valence by ten independent human raters. The researchers applied VADER sentiment tool to the COVID-19 corpus and the 'user timeline data.' The COVID-19 corpus was used to evaluate the overall sentiment of COVID-19 related tweets, and the user timeline data was used to assess the changes in user sentiment. To identify significant changes in twitter sentiments, they used Pruned Exact Linear Time (PELT). PELT algorithm attempts to identify change points in a given time series when strict conditions are satisfied. For the COVID-19 corpus, there were two PELT-identified significant change points, March 9th, 2020 (a few days before WHO declared COVID-19 as a pandemic), and March 19th, 2020 (few days after Donald Trump declared a national emergency). There was a significant increase in VADER sentiment after these change points, and there was also an increase in the percentage of positively scored tweets over time. Since the COVID-19 corpus only included tweets related to COVID-19, this sentiment score could not correctly represent people's well-being. Still, it could be a representation of how people and the media are discussing COVID-19. It could also be because of how people frame tweets about COVID-19. The researchers give an example of a tweet, "No matter how hard the situation nowadays during the pandemic outbreak, we should keep being positive and optimistic," these types of tweets would inflate the VADER sentiment score. However, this may not be a good representation of the users' emotions and well-being sentiments.

However, the user timeline data showed the exact opposite trend, VADER sentiment score decreased over time. There was also only one PELT-identified change, which was when Kobe Bryant (NBA player) died (his death was not related to COVID-19). The VADER sentiment score decreased during this time. There was another short drop-in sentiment right before March 9th (when WHO declared COVID-19 as a Pandemic). But overall people's sentiments were lower than before the pandemic hit, and did not return to the levels before the pandemic.

3.4 NRC Emotion lexicon

The NRC Word-Emotion Association Lexicon contains 10,170 lexical items and can detect eight emotions defined by Plutchik, Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, Trust [3]. He used the Syuzhet package version 1.0.1, which is freely available in R language has implemented NRC. This package classifies tweets into two sentiments: Positive, Negative, and the eight emotions defined by Plutchik. Then he used the function get_nrc_sentiment to analyze the tweets from the dataset he created. His sentiment analysis showed that USA was almost balanced between positive and negative sentiments. However, his emotion analysis showed that the USA, France, and China had the highest number of tweets with anger. However, one of the limitations of this study was that the tweets collected were only in English, although the 15 countries chosen for data collection were not all English-speaking countries. Another limitation was that NRC Lexicon does not take into account sarcasm and irony.

4 CONCLUSION

This literature review explored different ways of Analyzing Twitter Sentiments to predict people's overall well-being during COVID-19. First, I talked about why Twitter data is helpful to analyse people's sentiment and how researchers have used Twitter for different pandemic issues. Second, I talked about data collection and how there are differences and similarities between the datasets researchers used to predict the sentiments of the people during the pandemic. Third, I talked about different ways of Twitter Sentiment analysis. I also briefly talked about why researchers may prefer one sentiment analysis technique over the other, like preferring the RNN model over TextBlob, or choosing one type of dataset over other to predict the well-being of the people.

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