Harnessing Social Media Data to Measuring Mental Health Statistics

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Abstract:

According to the World Health Organization (WHO), mental health is "a state of well-being in which the individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his or her community". Mental health affects how we think, feel, and act. It also helps determine how we handle stress, relate to others, and make choices. There are feelings or behaviors can be an early warning sign of problem in mental health. They are feeling helpless or hopeless, having low or no energy, feeling unusually confused, forgetful, on edge, angry, upset, worried, or scared, yelling or fighting with family and friends, and experiencing severe mood swings that cause problems in relationships. Knowing this sign early can prevent negative impact that will occur. The problems is the mental health statistics using surveys is not up to date and costly.

Advances in information technology and data storage made social media data is an incredibly rich data source in both volume and variety. As of July 2019, Facebook has 2.38 billion users, Youtube 2.0 billion users, Instagram 1 billion users and Twitter 330 million users, contributing daily to billions of images, posts, videos and tweets. With social media being such a key part of everyday life and the data readily available online, it has the potential to change the way we collect information to understand society. Social Media such as Twitter, Facebook, and Instagram provide their data through their Application Programming Interface (API). We propose new method to measuring mental health statistics. We will utilize social media's API to crawl tweets or post which contains words about problem in mental health and place of origin user. Then, we using supervised machine learning approach to classify whether the words in tweets or post contain problem in mental health or not. This approach can be used to measuring mental health statistics.

Keywords: Application Programming Interface, Crawling, Classifying, Supervised Machine Learning, Mental Health

1. Introduction:

According to the World Health Organization (WHO), mental health is "a state of well-being in which the individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his or her community". Mental health affects how we think, feel, and act. It also helps determine how we handle stress, relate to others, and make choices. So, mental health will affect their physical health too. There are feelings or behaviours can be an early warning sign of problem in mental health. For example, feeling helpless or hopeless, having low or no energy, feeling unusually confused, forgetful, on edge, angry, sad, upset, worried, or scared, yelling or fighting with family and friends, and experiencing severe mood swings that cause problems in relationships. Knowing this sign early can prevent negative impact that will occur.

Mental health illness can be breakdown into several types, such as depression, stress, generalize anxiety disorder (GAD), social anxiety disorder, phobias, panic disorder, and mental disorders not otherwise specified (CMD-NOS) (Mental Health Foundation, 2016). In Indonesia have three classification about mental health, i.e. Schizophrenia and psychosis in the family, Emotional Mental Disorders, and Depression (Kementrian Kesehatan Republik Indonesia, 2018). But in this paper, we will just classified them into 4, depression, stress, GAD, and others.

1. Depression is a common mental disorder that presents with depressed mood, loss of interest or pleasure, decreased energy, feelings of guilt or low self-worth, disturbed sleep or appetite, and poor concentration, (WHO).
2. Stress is a response when we get a pressure because faced something challenging or dangerous and made us feels like frustrated and have a headache or the other effect.
3. GAD is a feeling that make some people feel extremely worried or feel nervous about these and other things—even when there is little or no reason to worry about them, like an over-anxiety (NIH).
4. The other illness that can't be classified into them.

The problem now is the mental health statistics using surveys is not up to date and costly. Even, the domestic agency has the publication of mental health, but the source of the data are from international agency like Mini International Neuropsychiatric Interview. So, we want to collect the other source to make some indicators that can show us how the condition of mental health in Indonesia is.

Advances in information technology and data storage made social media data is an incredibly rich data source in both volume and variety. As of July 2019, Facebook has 2.38 billion users, Youtube 2.0 billion users, Instagram 1 billion users and Twitter 330 million users, contributing daily to billions of images, posts, videos and tweets. With social media being such a key part of everyday life and the data readily available online, it has the potential to change the way we collect information to understand society. We will utilize social media's API to crawl tweets or post which contains words about problem in mental health and place of origin user. Now a days, all popular of social media platform have own rules to access their API. But, in this study we choose Twitter to support this paper because of their openness that can make us easy to crawl the data or get the json type data from Twitter API. Twitter is what's happening now. Twitter is an excellent platform for social science research as it provides a public record of peoples' attitudes, beliefs, and activities over a long time horizon (every public Tweet ever is in a searchable archive) (Zaydman, 2017). Twitter's developer platform provides many API products, tools, and resources that enable you to harness the power of Twitter's open, global, and real-time communication network. There also some reason we choose Twitter because of some perspective in Indonesia. Some people think that when we have something to say, something or emotion to share, we do and share that in Twitter. Meanwhile, if we want to show off and make some fake life, we will made a feed or stories in Instagram. The other problem is, in this time, some people diagnosed themselves into something hyperbole like depression or suicide or mental health illness because of simple thing, so we can't classified them into mental health illness directly. So, in this paper we do some manual classification first in some data to make sure the machine is accurate. This approach can be used to measuring mental health statistics, but the main purpose is not to substitute the data that available now, but to complement them, and to make sure the data can represent the mental health condition in Indonesia.

2. Methodology:

In purpose of constructing Mental Health Statistics from big data, we utilize Twitter API which is one of the popular Social Media in the world. We use the Twitter API endpoints, requests, and responses as part of the features in Twitter API. We research and build Mental Health Statistics in Indonesia. We apply four steps of processing, i.e. data acquisition, data pre processing, data classification, and data dissemination. The flowchart of those steps is depicted as follows:

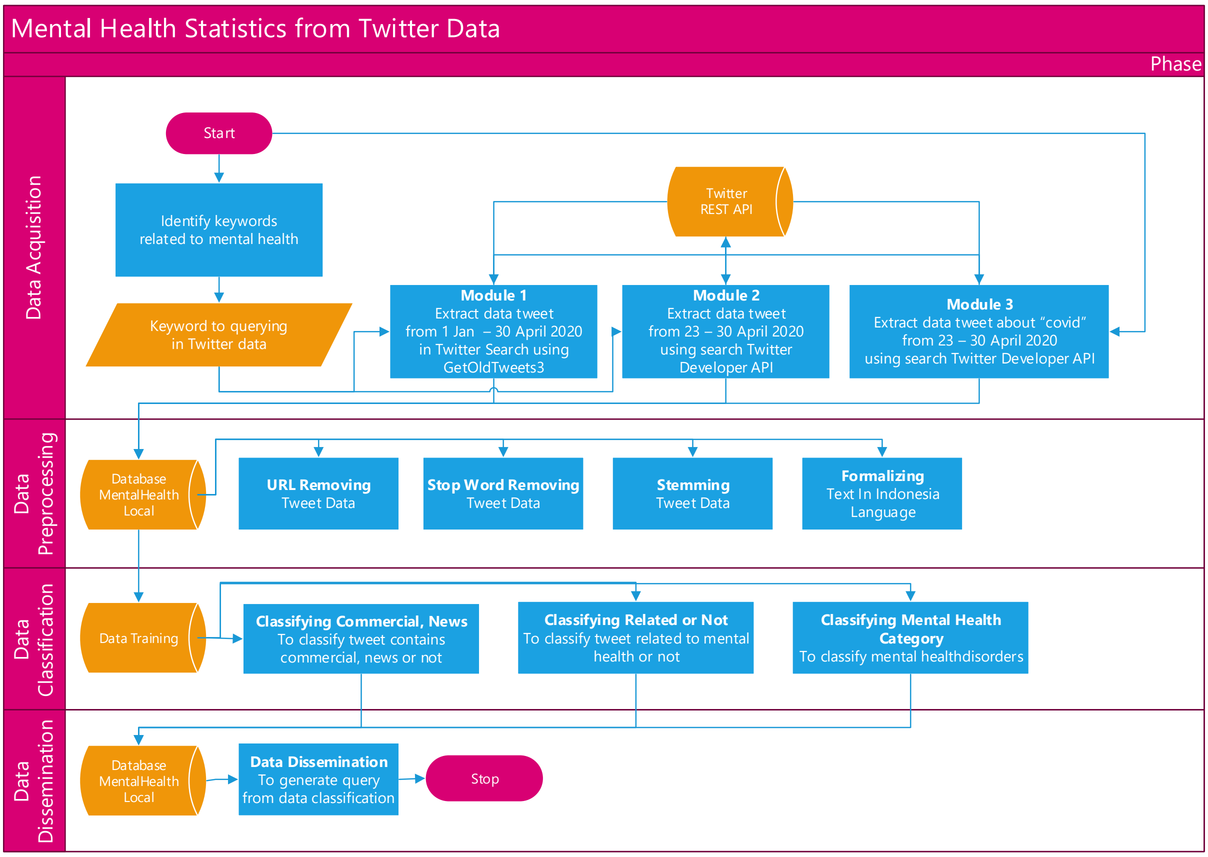

Figure 1. Step of Data Processing in Construct of Mental Health Statistics

1. Data Acquisition

In searching the data tweet, we identified several keywords that related to that related with mental health indicators. The list of keyword that we used to collect the data from Twitter is presented in the table below:

Table 1. List of keywords related to mental health indicators

No	Indonesia	English	No	Indonesia	English	No	Indonesia	English
1	anxiety	anxiety	11	gila	crazy	21	malas	lazy
2	bipolar	bipolar	12	hina	contemptible	22	marah	angry
3	bodoh	stupid	13	ingin mati	want to die	23	mental health	mental health
4	bunuh diri	suicide	14	insomnia	insomnia	24	menyerah	give up
5	capek	tired	15	jahat	evil	25	merasa salah	feeling wrong
6	cemas	anxious	16	kesehatan mental	mental health	26	posesif	possessive
7	cuek	ignorant	17	kesepian	lonely	27	pusing	dizzy
8	depresi	depression	18	ketagihan	hooked	28	putus asa	hopeless
9	disorder	disorder	19	khawatir	worry	29	sakit mental	mentally ill
10	gelisah	fidgety	20	lelah	tired	30	sedih	sad
31	stress	stressful	33	tersinggung	offended	35	tidak bahagia	not happy
32	susah tidur	insomnia	34	tertekan	depressed	36	tidak suka	do not like
						37	trauma	trauma

We using python language to build the system that collect, classify, and disseminate the data tweet from Twitter API. We also using Mysql for DBMS (Database Management System) that stored the extracted data tweet from Twitter API. We using three schemes for extracting the data tweet from Twitter API:

a. Modul 1: We created module to collect the old tweet with library GetOldTweets3. A Python 3 library and a corresponding command line utility for accessing old tweets. Twitter

Official API has the bother limitation of time constraints, we can't get older tweets than a week. So, we using this library to search query for 37 keywords in 11 cities in Indonesia. The cities are Bandung, Bekasi, Bogor, Depok, Jakarta, Makassar, Semarang, Solo, Surabaya, Tangerang, and Yogyakarta. We pick out that cities because the volume of tweet around their area is high and they became the city with the highest covid-19 (Corona Virus Diseases 19) case. We also want to know how COVID-19 breakout affect the mental health. We collected the data tweet from 1 January 2020 until 30 April 2020 by each keywords.

b. Modul 2: We created module to request the endpoints Twitter API (Application Programming Interface). We used standard tiers of search APIs that provided by Twitter API Developers. We used search Tweets features from Twitter API. This search API searches against a sampling of recent Tweets published in the past 7 days. Part of the 'public' set of APIs. We also set the query to return the tweet topics near a specific latitude, longitude location. We using library python Tweepy. An easy-to-use Python library for accessing the Twitter API. The duration of date is from 23 - 30 April 2020. We used parameters location out of 12 provinces and in central of capital city each province.

c. Modul 3: We created module to request the endpoints Twitter API that contains tweet about COVID or COVID-19. The duration of date is from 23 - 30 April 2020.

2. Data Pre Processing

In this stage, we created module to cleaning the tweet data. Text data needs to be cleaned and encoded to numerical values before giving them to machine learning models. The following steps we take in this stage are:

a. **URL Removing**: we create function to detect url text and then we removed it.

b. **Stop Word Removing**: we use Sastrawi library in python. Sastrawi is a simple Python library which allows you to reduce inflected words in Indonesian Language (Bahasa Indonesia) to their base form (stem). We used stopWordRemoverFactory from the Sastrawi module.

c. **Stemming**: Stemming is the process of removing word inflections into their basic form. To do stemming in Indonesian we can use Sastrawi lib again.

d. **Formalizing**: Formalizing is the process to change words that are not standard to standard in accordance with Indonesian language rules. The tweet that we classified processing then is only contains the formal word. We used REST API Pujangga, Indonesian Natural Language Processing REST API. An interface for InaNLP and Deeplearning4j's Word2Vec for Indonesian (Bahasa Indonesia) in the form of REST API. This REST API run with Scala programming language. Then we create module in our system with python language to request continually to the server of Pujangga REST API. Then we stored the data tweet after formalizing in our database.

3. Data Classification

The main stage of this study is in here. We constructed three data classification modules:

a. Classifying Commercial, News: To classify tweet contains commercial, news or not. We only used the tweet that no contain both commercial and news. We conduct the data training from sample tweet that we extracted. We used 5.069 data tweets that we classified manually one-by-one with sample of commercial tweets is 4.350 and non commercial or not news tweet is 719. We used Naïve Bayes Classifier with sklearn library python. The data training got the score of accuracy about 0.6831395. Because that accuracy rate is quite high so the results of the classification is also reliable.

b. Classifying Related or Not Related: To classify tweet related to mental health or not. We used 1.719 data tweets that we classified manually one-by-one with sample of related with mental health topic tweets is 799 and not related with mental health is 920. We also used Naïve Bayes Classifier with sklearn library python. The data training got the score of accuracy about 0. 939842. Because that accuracy rate is quite high so the results of the classification is also reliable.

c. Classifying Mental Health Category: To classify tweet that related to mental health to category in mental health disorders. We used 7.852 data tweets that we classified from classify point b and then we categorized manual to 4 category, i.e. depression, stress, generalised anxiety disorder (GAD), and common mental disorders not otherwise specified (CMD-NOS). We categorized sample of depression tweets is 3.588, stress tweet is 950, GAD is 726, and CMD-NOS is 2.588. We also used Naïve Bayes Classifier with sklearn library python. The data training got the score of accuracy about 0. 906517. The accuracy rate is also quite high so the results of the classification is also reliable.

2. Result:

By using system which we have developed for construct mental health statistics, the result of data acquisition, data pre-processing, data classification, we stored in our database. This is the result that we disseminate from our module planning:

a. Modul 1: In period 1 January – 30 April 2020 we managed to collect tweet in mental health indicators. We collected 469.117 tweets along the period, which 78.236 tweets in January, 66.373 tweets in February, 75.265 tweets in March, and 249.243 tweets in April. The number of these tweets that not contains commercial or news there are 177.725 tweets, which 29.358 tweets in January, 25.377 tweets in February, 27.636 tweets in March, and 95.354 tweets in April. Then from this number we categorized into have related with the mental health indicator or not. There are 89.408 tweets that have relation with mental health indicators, which 14.802 tweets in January, 13.315 tweets in February, 14.833 tweets in March, and 46.458 tweets in April. Figures 2 shows the trend of mental health disorders increased steadily from beginning period and there has been a significant increase in end period.

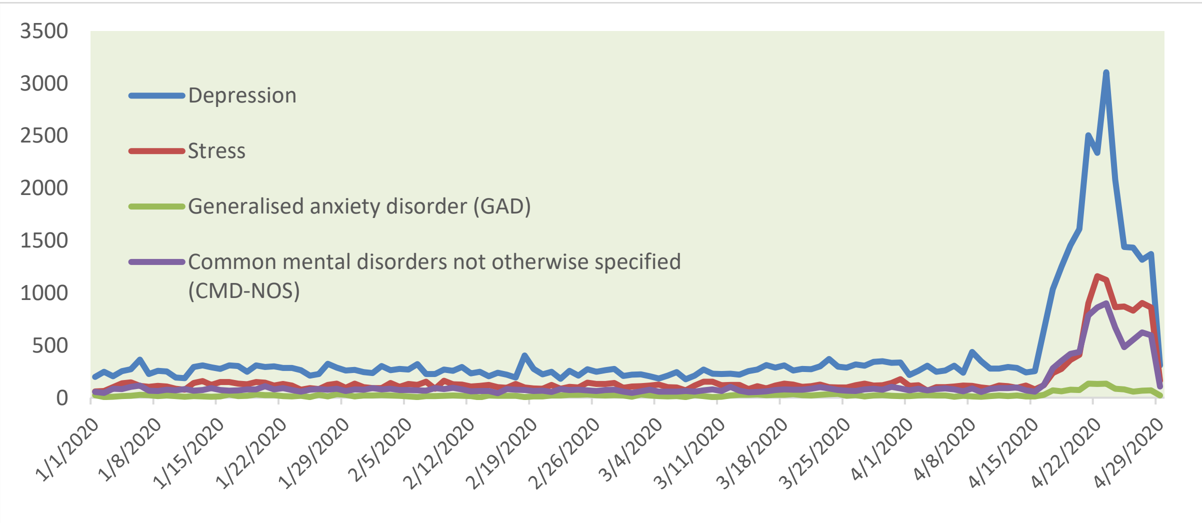

Figure 2. The number of tweets related with mental health indicators in Indonesia

b. Modul 2: In period 23 - 30 April 2020 we managed to collect 386.695 tweet in mental health indicators by using Twitter API. After we classified the data we got 144.390 tweets among the period. In Figure 3 we found that keyword sadness is rise steadily from 10.759 tweets to 15.284 tweets in eight days. This keyword fall in three days first in this period, then increase steeply until 27 April 2020 had drop dramatically. After this day the graph go up until end period. Meanwhile, keyword depression is founded rise steadily.

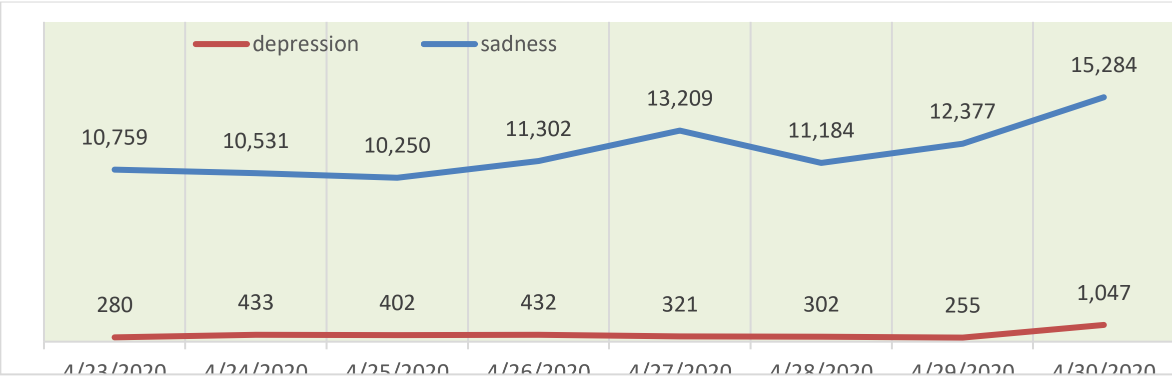

Figure 3. The number of tweets related with mental health indicators in Indonesia, 23 – 30 April 2020

c. Modul 3: In period 23 – 30 April 2020, we collected tweet that contains keyword "COVID or COVID-19". We found about 101.899 tweets, and 100.851 commercial or news about this keyword. The rest about 149 non-commercial or non-news tweets, 63 tweets is contains mental health indicators. There are tweets are 18 tweets in Jawa Barat and 15 tweet in Banten.

3. Discussion, Conclusion and Recommendations:

Based on the result, we have several findings. First, we developed tools and method to identify potentially relevant content in mental health indicators. This research took the large unstructured data source of Twitter and searched for the content that is relevant to mental health. The result shows that we can use Twitter data to construct the indicator for measuring mental health statistics. Second, to increase the accuracy of the data training that code by human manually, we needs automated methods that will replicate human coded examples. Third, the results of the Twitter analysis shows the nature of the human conversation about mental health disorders. Knowing this sign early can prevent negative impact that will occur.

There are also recommendations to explore other social media platform such as Facebook, Youtube and Instagram more deeply in order to measuring indicator of mental health statistics. Examining the characteristics and sentiment of the classified text data. Developing a robust search strategy in social media to get relevant data about mental health.

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