MENTAL HEALTH TWEETS CLASSIFICATION IN KENYA

You can find links to our Mental Health Tweets Classification github repository, presentation slides and project management tool here: Github, Powerpoint, Jira.

1. Business Understanding:

Background

In Africa, most of the people with serious mental health disorders do not have access to treatment that they need. There is a huge gap in accessing healthcare when it comes to mental health related illnesses & Covid-19 has also not helped the situation, having caused a rise in the number of mental health related issues.

A WHO report showed that Kenya was among the few states that did not allocate a separate budget for mental health, with a government expenditure that accounted for only 0.01% of the total budget. This translates to lack of adequate facilities, as witnessed by the audit on mental health by the Auditor General. This audit showed that a whooping 22 out of 47 counties in Kenya do not have psychiatric units.This means that all the patients in need of mental health care have to be referred to Mathari National Hospital, the only national hospital specializing in mental health.

It has been estimated by mental health experts that 1 in every 4 Kenyans may be suffering from a mental health related issue, ranging from depression, to anxiety, or even bipolar disorder. A key challenge we face is the low level of awareness of mental health disorders, and in particular the symptoms associated with each.

Problem Statement

On June 12th 2021, Dr. Lydia Wahura committed suicide in her car after leaving an ongoing class at University of Nairobi. This shed a light on the ongoing mental health crisis in the country. A World Health Organization report released recently ranked Kenya position five among African countries with the highest number of depression cases.

Kenya has a culture of denial in mental health issues, which only serves to make things worse. The pandemic has had a substantial negative impact on mental health. However, there is still no formal mental health response plan, with the state only declaring its commitment to mental health. The lack of a formal mental health response plan is largely influenced by the assumption that other diseases make up the biggest threats in the country, which is increasingly becoming a fallacy, if the statistics on the causes of death in the nation are anything to go by.

We would like to find out the main disorders that Kenyans are currently struggling with, based on their conversations on twitter. We will scrape data from Kenyan twitter users and do classification between the different mental health disorders.

Business Impact

Since the studies by the WHO confirmed that the government does not have a formal mental health response plan. This study will assist the government to map out the proportions of people suffering from different disorders, so as to adequately plan for the restocking of drugs that may be used by people suffering from the different disorders.

Furthermore, the government will be better prepared to set up counselling centers, and raise awareness of the same social media platform on the different mental illnesses. These drugs are usually very expensive and hard to find for most common illnesses.

This will be factored in by the government as it develops its formal mental health response plan.

Business Objectives

a. **Main Objective**

To aid in mapping out the proportions of people suffering from different mental health disorders in order to set up counselling centers, and raise awareness of the same on social media platforms.

b. **Specific Objectives**

1. To find out which mental health disorders are most rampant in Kenya.
2. To create a model that will predict mental health categories.
3. To find out the frequency of occurrence of these disorders in our tweets.

Assessing the situation

a. **Resources**

Inventory of Resources

i) Tweepy Twitter Scraping tool:

ii) Software

- Github
- Google collaboratory
- Libraries(Pandas, Numpy, Seaborn, Matplotlib, Tensoflow)
- Jira
- WandB
- Streamlit

b. **Assumptions**

i. The information scraped is accurate.

c. **Constraints**

i) Some of the users used several hashtags on mental health on a tweet, making it difficult to classify the tweet.

ii) Some users had tweets whose content was not consistent with the hashtags indicated on the tweet.

iii) Some locations are indicated on the dataset with different names e.g Nairobi, Kenya & Nairobi. Some are completely erroneous e.g ‘wewe uko wapi’

Data Mining Goals

1. To Identify mental health disorders that are most common in our dataset.
2. To create a model to predict the mental health disorders
3. To plot the frequency of occurrence of these disorders in our tweets.

2. Data Understanding:

Overview

The dataset comprises tweets by Kenyan users on Twitter on different mental health disorders such as depression, anxiety, suicidal ideation, paranoia, autism, dementia, bipolar disorder & schizophrenia.

Collecting initial data

Data was scraped from twitter using Tweepy tool, with a filter used on the different mental health disorders. It contains data for the last 7 days, due to the restrictions provided while using Tweepy.

Describing and exploring the data

We scraped the data on the different tags, then concatenated them into one final dataset.

The final dataset contains 756 rows and 13 columns, as follows:

Column	Definition	Measurement of the variable
user	User who tweeted	Object
tweet	Content of tweet	Object
location	Twitter user's location	Object
description	Twitter user's bio description	Object
friends_count	Number of users being followed by the twitter user	Object
followers_count	Number of users following the twitter user	Object
statuses_count	Number of statuses created by the user since inception of their account	Object

created_at	Date when the tweet was created	Object
retweet_count	Number of retweets the tweet received	Object
hashtags	Hashtags on the tweet	Object
disorder	Mental health disorder	Object

Verifying data quality

All columns except the location & description columns had no null values. The description column has 28 null values while the location column has 3 null values. There was no evidence of inconsistencies in the data.

3. Data Preparation:

Selecting Data

Steps taken during our data exploration are as follows :

- Scraping data from twitter using Tweepy.
- We used data frames to load data from the scraping exercise and analyse it statistically to produce quality output results.
- Concatenated the datasets into one dataframe for ease of analysis.

Cleaning Data

Data cleaning procedures that were be performed on our dataset include:

i. Duplicates: Checking for duplicates in our data There were no duplicates in the dataset.
ii. Missing Values: Identifying and dealing with missing values within our dataset. The description column had 28 null values and the location column had 3 null values. These columns were all removed because we are not using them in our analysis.
iii. Dropping irrelevant fields: We dropped the 'friends_count', 'user', 'followers_count', 'statuses_count', 'retweet_count' & 'hashtags' columns as they were irrelevant for our analysis.
iv. Renaming Columns: Using the same pattern for column names. Making sure all columns are in lower case.
v. Data types: Checking the column data types and making sure they are the appropriate data types. We converted the ‘created_at’ column to datetime format.

Data Pre-processing

We covered the following steps in data preprocessing to prepare our data for text classification:

- LabelEncoding: label encoded our ‘disorder’ column to convert the values to numerical values.
- Changing all values in the ’tweet’ column to lowercase for consistency in analysis.
- Removing our punctuation marks and replacing them with spaces.
- Removing words from our dataset that begin with ‘http’.

- Removing stop words in our dataset. We added more words to the stop words list from the nltk package, which are common stop words in Swahili.
- Tokenizing the pre-processed data.
- Lemmatizing the data, reducing them to their base words.

Data Augmentation

The disorders in our dataset had a class imbalance since the data was distributed as shown:

Disorder	**Number of Entries**
Depression	353
Anxiety	278
Suicidal	59
Bipolar Disorder	17
Schizophrenia	14
Autism	14
Dementia	12
Paranoia	9

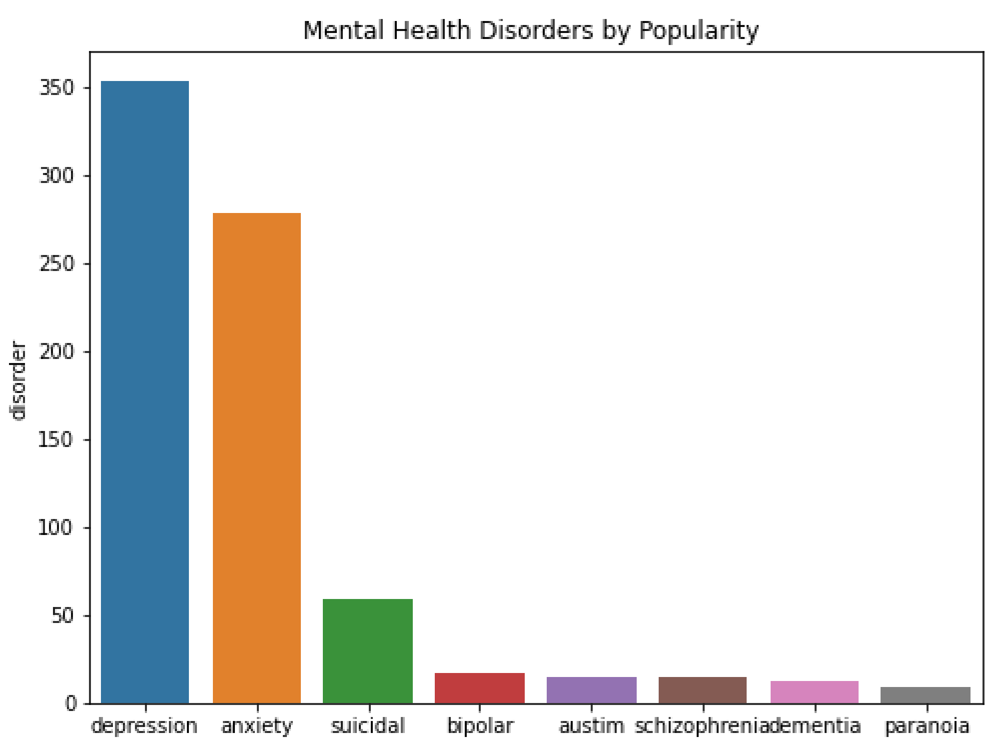
We used NLP Aug to augment our data to 300 entries each for the disorders to get rid of the class imbalance.

4. Exploratory Data Analysis:

To display and comprehend our data, we generated bar charts and word clouds. From the univariate analysis we found that:

- Tweets on depression had the highest proportion with anxiety having the second highest proportion and paranoia had the least number of tweets followed by dementia.
- Kenyan twitter users mostly tweet about mental health disorders in the morning hours with the most number of tweets at 7am and 8am.The lowest number of tweets on mental health are observed between 11pm and 12am.This maybe due to the fact that most users are asleep at that time.
- On the depression dataset the mostly used words were; depression”,”people”,”arsenal” among other words.
- On the anxiety dataset the mostly used words were ;”anxiety”,”depression”,”people” among other words.
- On the suicidal dataset we found out that the most used words were; ”suicidal”,”thoughts”,”life” among other words.

The figure below shows a summary of the mental health categories detailed above:



5.Modelling

From the exploratory data analysis, it was noted that there was class imbalance amongst the models and we therefore used Natural Language Processing Augmentation to solve this problem.

We run the following models on our data;

- Multinomial Naive Bayes Classifier
- Support Vector Model.
- Logistic Regression,
- Recurrent Neural network
- Bert Transformer.

We tracked the performers of our model using the WandB.

The models performed as follows:

1. **Naive Bayes Classifier -Multinomial**

Class Name	Precision	Recall	F1 Score
Depression	**0.82**	**0.75**	**0.78**
Suicide	**0.88**	**1.00**	**0.94**
Bipolar	**0.93**	**0.96**	**0.94**
Dementia	**0.95**	**1.00**	**0.97**
Anxiety	**0.81**	**0.67**	**0.74**
Autism	**0.97**	**1.00**	**0.99**
Schizophrenia	**1.00**	**1.00**	**1.00**
Paranoia	**0.94**	**0.98**	**0.96**

Overall accuracy of 91%

2. **Logistics Regression**

Class Name	Precision	Recall	F1 Score
Depression	0.86	0.82	0.84
Suicide	0.95	1.00	0.97
Bipolar	0.94	0.96	0.95
Dementia	0.98	1.00	0.99
Anxiety	0.82	0.80	0.81
Autism	1.00	1.00	1.00
Schizophrenia	1.00	1.00	1.00
Paranoia	0.98	0.98	0.98

Overall Accuracy 94%

3. **Linear Support Vector**

Class Name	Precision	Recall	F1 Score
Depression	0.85	0.81	0.83
Suicide	0.95	1.00	0.97
Bipolar	0.96	0.96	0.96
Dementia	0.98	1.00	0.99
Anxiety	0.81	0.78	0.79
Autism	1.00	1.00	1.00
Schizophrenia	1.00	1.00	1.00
Paranoia	0.97	0.98	0.98

Overall Accuracy 94%

4. **Recurrent Neural Network**

5. **BERT Transformer**

Class Name	**Precision**	**Recall**	**F1 Score**
Depression	**0.76**	**0.86**	**0.81**
Suicide	**1.00**	**0.40**	**0.57**
Bipolar	**1.00**	**0.80**	**0.89**
Dementia	**0.50**	**0.50**	**0.50**
Anxiety	**0.84**	**0.85**	**0.84**
Autism	**0.00**	**0.00**	**0.00**
Schizophrenia	**1.00**	**0.50**	**0.70**
Paranoia	**1.00**	**0.71**	**0.83**

Overall Accuracy: 82%

6. Conclusion

We noted that the model that performed better was Logistics Regression. It predicted all the mental health categories with a precision score of close to 1 for five classes and two of them had a precision score of 1. We further noted that most Kenyans from the scraped data suffer from depression

7. Recommendations:

From the findings above, we therefore recommend creation of counselling centers, and raise awareness of the same on social media platforms.

Links:

1. **Github link is found here**
2. **Wandb link for:**
    - **Recurrent Neural Network model is found here**
    - **Multinomial model link**