MAKING THEIR FEELINGS KNOWN: EMOTIONAL ANALYSIS OF SOCIAL MEDIA DATA ON LOCK DOWN IN NIGERIA

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ABSTRACT

Twitter a social media platform has become a generally accepted medium used by individuals to express sentiments, opinion and emotions about a particular product, institution, individual, government policies, among others. However, analysis of the emotions expressed on social media is hardly researched. This study aims to establish that the emotion expressed towards a policy reveals the depth of their sentiments towards the policy, and it determines their action. One of the objectives is to explore emotions expressed in the tweets posted by residents of four states in Nigeria (Abuja, Lagos, Ogun and Kano state) where the federal government total lockdown was enforced as a non-pharmaceutical measure of reducing the spread of the novel coronavirus. This study collected 22468 tweet messages that contained the keyword "lockdown" called Naija4StatesLockDownTweets. Using labelled (joy, anger, sadness and fear) emotion dataset to be trained on SGD Classifier, a 92% accuracy was obtained on the train dataset. Then, the study dataset was tested on already trained SGDC classifier for an emotional analysis. The result obtained revealed that majority of twitter users, across the four states, were not happy about the lockdown. Fear had 32.8% of the Naija4StatesLockDown dataset, 29.74% anger, 19.99% joy and 17.47% sadness. Hunger and lack of social welfare infrastructure are some of the reasons behind the dominance of anger and fear. These negative emotions are suspected to be the reason why the virus continued to spread despite the lockdown. The study strongly recommends that government should establish a well-structuredsocial welfare program for citizens.

Keywords: COVID-19, Emotion Analysis, Lockdown, SGD Classifier

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Introduction

It has become necessary to identify sentiments beyond the borderlines of positive, negative and neutral sentiments. Hence, there is need for emotional analysis. Emotions determine our impression of the world and how we make our day to day decisions. They are sophisticated and have underlying meaning (Mohammad & Kiritchenko, 2018). Arousal of emotion influences behaviour. It also often affects how we reason. Emotions have certain motivational components. For instance, a state of happiness simulate a person to make impact or achieve much more while a state of gloominess discourages an individual from making head ways (Popa, 2019; Sincero, 2012).The use of social media content for research is on the increase (Gerard & Spring, 2017; Khatoon, Aisha Banu, Zohra, & Chinthamani, 2019; Yinka, Adesope Rebecca Queendarline, 2018). Its usage ranges from sentiment analysis, opinion mining, thematic analysis, subjectivity analysis and so on. There has been a proliferation of social media usage across the globe for the articulation of opinions on matter of local and national importance. With the outbreak of novel coronavirus, there is currently a surge in its usage. This is because there is always a surge in information proliferation during disasters or national issues such as the coronavirus pandemic that is currently ravaging the world (Frenkel et al., 2020; Wiederhold, 2020).The novel Severe Acute Respiratory Syndrome Coronavirus

(SARS-CoV-2) also known “COVID-19” was declared an epidemic by the World Health Organization(World Health Organization, 2020). The virus was detected in Wuhan China in December 2019, as at 22nd of July, 2020 there has been 15,120,787 coronavirus cases, 620,265 deaths and 63,675 of its victims being in critical conditions in 213 countries and territories (Adhikari *et al.,* 2020; WorldOMeter, 2020). Nigeria's first case of the virus was reported on the 24th of February 2020 (Nigeria Centre for Disease Control, 2020a; Oyeniran & Chia, 2020). Lockdown and social distancing, a non-pharmaceutical measure of reducing the spread of the virus, which has been proven to be effective in several countries including China, Iran, Italy, amongst others was implemented in Nigeria (Ehijiele, 2020; Zhong *et al.*, 2020).

The President of Nigeria, Muhammadu Buhari GCFR, on 29th of March, 2020, declared total lockdown effective from the 30th of March, 2020(Kola, 2020). It affected three states of the federation where the majority of the COVID-19 cases emanated. The number of reported coronavirus cases as at that time was 125 across only 12 states of Nigeria (Nigeria Centre for Disease Control, 2020b). In Kano state, the enforcement of the lockdown policy commenced 28th of April, 2020 as a result of mysterious deaths which were later traced to be related to COVID-19 (Adejoro, 2020; Brown, 2020).

However, as at 12th of April, 2020, two weeks after the lockdown commenced in 3 states, the total number of coronavirus cases in Nigeria had risen to 323 cases (158.4 % increase) across 20 states (Nigeria Centre for Disease Control, 2020b). Also in Kano, as at 27th of April, the total number of coronavirus cases reported in Kano was 102, but by 11th of May, the state had become the second most infected state in Nigeria with 679 coronavirus cases, a565.69% increase(Nigeria Centre for Disease Control, 2020b).This implies that the lockdown was not effective in reducing the spread of the coronavirus in Nigeria, despite its negative impact on the nation's economy.

Armed with the information that more people were active on social media during the lockdown period (Frenkel et al., 2020), the vast amount of social media's content based researches (Gerard & Spring, 2017; Khatoon *et al.,* 2019; Yinka, Adesope Rebecca Queendarline, 2018) and the knowledge that emotions influences behaviour (Boyd, 2020; Popa, 2019; Sincero, 2012).

In the work of Wiederhold, (2020), he asserted that a quarter of US and UK users on Facebook and Twitter had increased their usage of these platforms. It also reported that there has a been a 20% increase in web traffic between 8th and 15th of March, 2020. This is an indicator that many people used these platforms not only to stay informed but also to keep themselves occupied. Therefore, it is pertinent for researchers, health professionals and other stakeholders to analyse and gain new insight from messages exchanged on social media platforms. Analysing these messages can help them to have a better understanding of people's reaction and strategize appropriately.

Also, Manguri, Rasul, & Amin (2020) carried out a research on the sentiment analysis using the two key words namely: #CORONAVIRUS and #COVID-19 to retrieve tweet. Text Blob, a python-based library was used for the sentiment analysis. The goal was to determine the polarity and subjectivity scores of each of the tweets that made up their dataset. 530,232 tweets were retrieved from twitter using Tweetpy. The polarity score revealed that 36% of the tweets expressed optimism, 14% were negative while 50% were neutral. Subjectivity score indicated that 64% of the tweets were objective, 22% subjective and 14% were neither subjective or objective. It concluded that the sentiments towards COVID-19 varied on daily basis.

However, Chakraverty, Srishti, & Bhalla, (2017) developed an emotion analysis lexicon which determined emotion that is predominant in a text, emotional intensity and emotional trend. The focus of the research was to determine the state of mind of Twitter users based on the messages they share on the platform. Emotion data for the research was sourced from Parrott's List of emotions REF, WordNet REF, Emoticons and Internet Slangs. These were used to build lexicon for love, anger, fear, joy, sadness and surprise, which are the basic human emotions. Tweets from New York, Las Vegas and Boston all in the USA were collected using their geocoordinates for the purpose of the research. It suggested that microblog driven emotion analysis reveals the origin, transition and progression of emotional states in a particular society.

Salinca, (2015) explored two methods of feature extraction and four machine learning models, towards automating the process sentiment analysis of business reviews. It made use of yelp challenge dataset, which was made up of 1.6 million reviews from 366,000 users. Naïve Bayes, Linear SVC, Logistic Regression and SGD Classifier were the machine learning models implemented. SGD Classifier outperformed other models in all variations of features achieving 94.4% in one of the feature combinations. The result of these experiments does not relate the emotion of individuals with their actions. In our approach we implemented the principles of Salinca, (2015) in the training of the SGD Classifier, to improve on the sentiment analysis experiment of Manguri, Rasul, & Amin (2020) towards being able to determine the actual emotions expressed in tweets by residents of the Nigerian states selected for the study. The goal of the study is to develop a SGD

Classifier based emotion identification machine learning model that can detect joy, sadness, fear and anger in our lockdown themed tweets shared on twitter by residents of Ogun, Lagos, Abuja and Kano states of Nigeria.

Materials and Methods

In this section, we describe the process of collecting lockdown themed tweets originating from 4 states in Nigeria namely Abuja, Kano, Lagos and Ogun using GetOldTweets3, a python library. The collected tweets were called Naija4StatesLockDownTweets. The process of designing a SGDClassifier based machine learning model was also explained. The model called EmoDet, was trained and tested using (Mohammad & Bravo-marquez, 2017)'s Emotion Intensity Dataset for tweets. Finally, an emotional analysis of our data was conducted using the model.

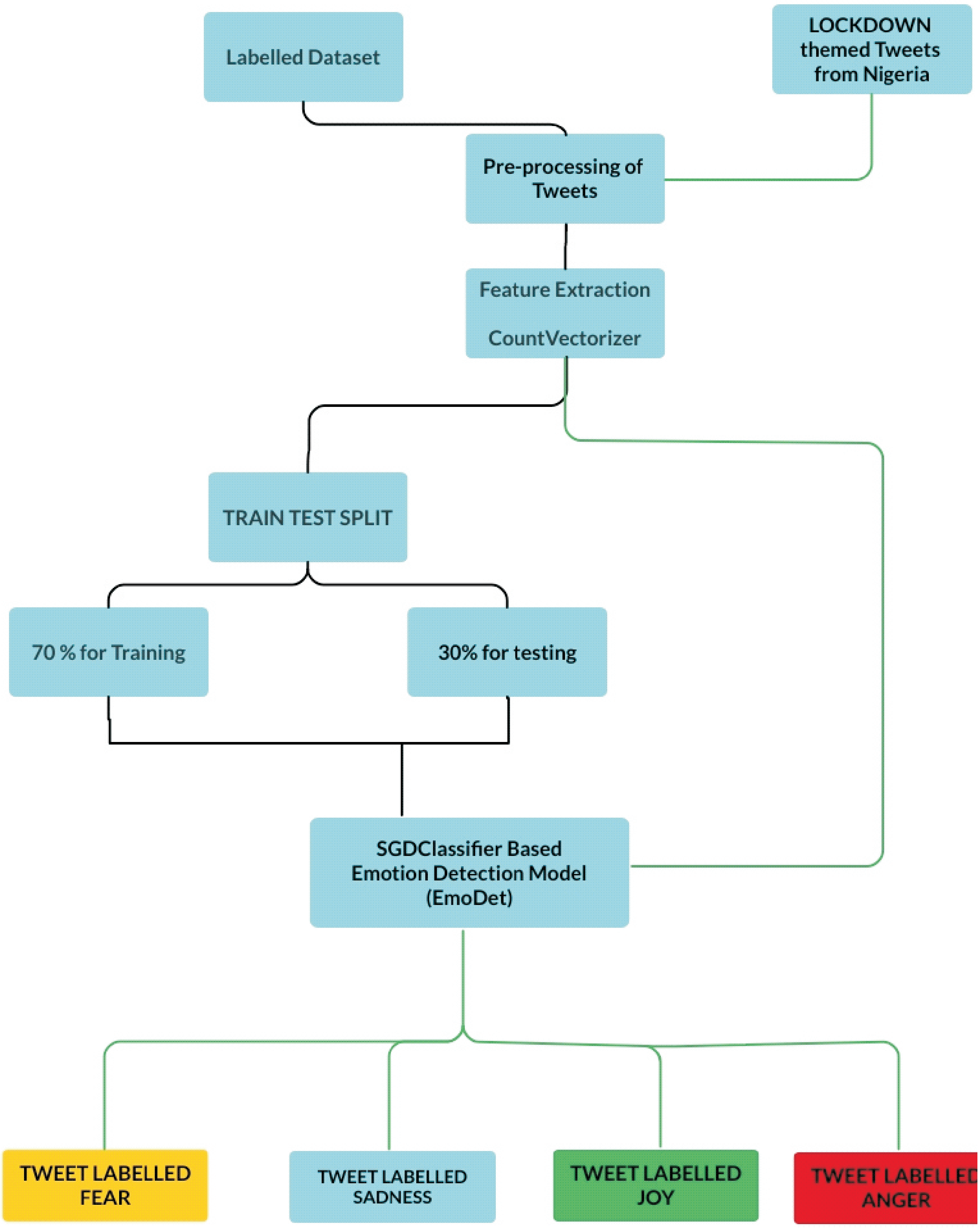

Figure 1 The process of emotion detection by our EmoDet Model

Dataset

This research work made use of two different datasets as shown in Figure 1 above. The first dataset is the emotion intensity dataset curated by . The dataset provides information on the id of the tweet, the tweet, emotion i.e. joy, sadness, fear and anger, lastly it provides information on the intensity of the emotion being expressed in this model. The dataset was used for the training of the SGDClassifier based classification model. Our EmoDet model was trained using the tweet column while emotion was adopted as the label because one of the aims of this study is label the tweets as joy, sadness, fear or anger. The dataset had a total of 5,997 tweets with 1,701 tweets labelled as anger; 1,616 tweets labelled as Joy; Sadness had 1,533 tweets while fear had 1,147 tweets. These labels are regarded as classes. Figure 2 shows the percentage distribution of each classes

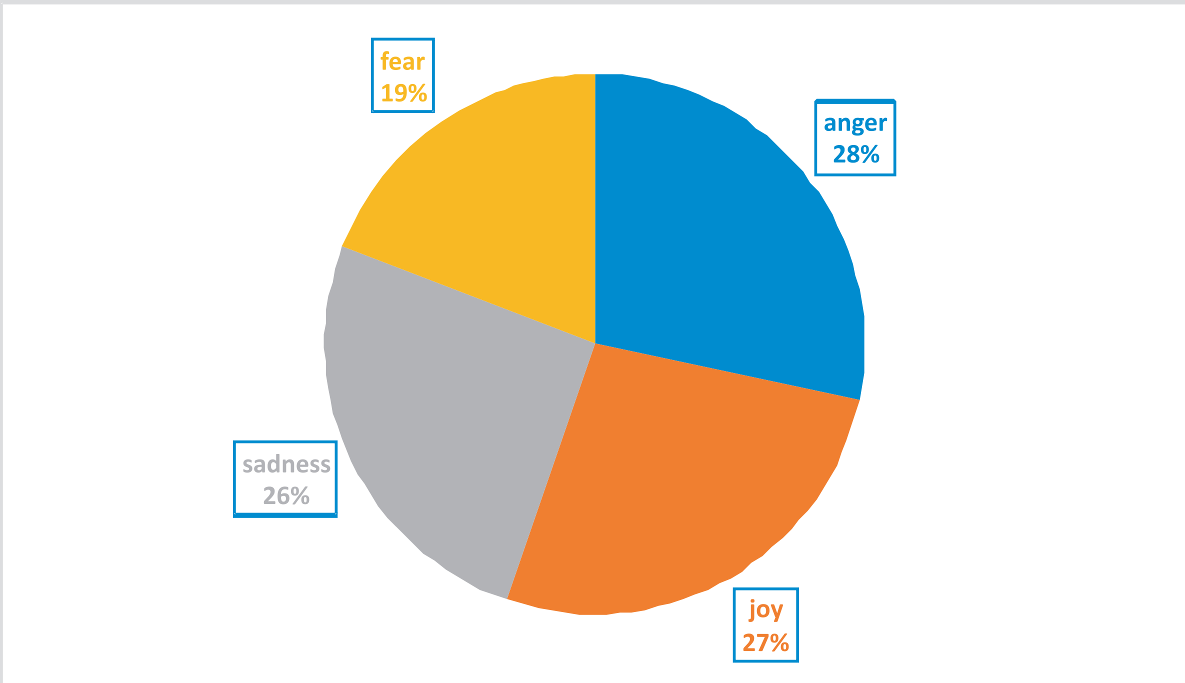

Figure 2: Label Distribution of the labelled Dataset. (Source: (Mohammad & Kiritchenko, 2018))

In this paper, the second dataset used is the Naija4StatesLockDownTweets. It is a collection of location-basedtweets containing the keyword "lockdown". GetOldTweets python library has been utilized for extraction of tweets from Twitter. GetOldTweets allows for tweet retrieval using keywords, hashtags, timelines, or geo-coordinates (latitude and longitude).This research was targeted at four Nigerian states, which are Abuja, Lagos, Kano and Ogun using geo-coordinates of major locations in the state and specifying a radius of 50km from the chosen geo-coordinates as summarized in table 1. Despite the numerous restrictions from Twitter, we kept retrying to enable us extract as many tweets as possible. Across the four Nigerian states, 22,468 tweets have been extracted regarding LOCKDOWN keyword form 29th March to 11th of May. For each state, tweets were retrieved for only fifteen days, this started from the day that preceded the kick-off of the lockdown policy implemented in the state, table 1 provides details. The difference in the start date of each state is because the lockdown policy was kicked off at different dates in each of the states except Lagos and Abuja that started on the 30th of March. The collected tweets were saved in CSV (Comma Delimited) file format, pre-processed, feature extracted and fed to our Emotion Detection model for it to provide an emotional label for the tweet.

Table 1: Total Lockdown date and coordinates of four Nigerian states

State	Start – End Date	Coordinates	Radius (Km2)	No. Of Tweets
Abuja	29th March– 12th April, 2020	9.06146, 7.50064	50	5,473
Lagos	29th March– 12th April, 2020	6.55086, 3.29804	50	6,534
Ogun	3th April – 17th April, 2020	6.82364, 3.91846	50	6,502
Kano	27th April– 11th May, 2020	11.99997, 8.53486	50	3,959
TOTAL				22,468

Table 2 presents the information on the number of tweets shared per day in each state. Tweets posted within the period of the 29th of March, 2020 to the 12th of April, 2020 in Abuja and Lagos are 5,473 and 6534 tweets respectively. In Ogun state, a total of 6,502 Twitter messages (tweets) containing the keyword "lockdown" was shared between 4th of April, 2020 to the 17th of April, 2020. Finally, in Kano the total number of lockdown-based tweets between the 27th of April to the 11th of May, 2020 are 3,959 tweets. Lagos had the highest number of tweets taking about 29.08% of the total number of tweets, followed by Ogun, Abuja then lastly by Kano accounting for only 17.62%.

Table 2: Breakdown of Tweets per day for each state

DATE	ABUJA	LAGOS	OGUN	KANO	TOTAL
29/03/2020	493	403	0	0	896
30/03/2020	182	1,850	0	0	2,032
31/03/2020	665	557	0	0	1,222
01/04/2020	573	405	0	0	978
02/04/2020	430	325	0	0	755
03/04/2020	403	405	255	0	1,063
04/04/2020	319	302	290	0	911
05/04/2020	391	458	330	0	1,179
06/04/2020	414	432	389	0	1,235
07/04/2020	391	364	280	0	1,035
08/04/2020	446	411	316	0	1,173
09/04/2020	437	411	344	0	1,192
10/04/2020	100	59	336	0	495
11/04/2020	116	91	421	0	628
12/04/2020	113	61	346	0	520
13/04/2020	0	0	1,067	0	1,067
14/04/2020	0	0	610	0	610
15/04/2020	0	0	496	0	496
16/04/2020	0	0	514	0	514
17/04/2020	0	0	508	0	508
27/04/2020	0	0	0	739	739
28/04/2020	0	0	0	380	380
29/04/2020	0	0	0	270	270
30/04/2020	0	0	0	320	320
01/05/2020	0	0	0	293	293
02/05/2020	0	0	0	260	260
03/05/2020	0	0	0	224	224
04/05/2020	0	0	0	307	307

Data Pre-Processing
The following pre-processing was done to the data after the download. of the tweets. Then, the following tasks were

i. Removal of Hashtags
ii. Removal of Universal Resource Locators (URLs)
iii. Checked for duplicates.
iv. Removal of non-text characters
v. Removal of repeated words.
vi. Make all letters to be lowercase
vii. Remove punctuation and symbols
viii. Lemmatisation of words.
ix. Correction of Letter repetition: This ensures that there is no repetition of any letter more than twice. It converts Cooooooool to cool.
x. We also removed the 10,000 rarest words appearing in the dataset.

Feature Extraction
This section describes the vectorisation process and function. All of the tweets were converted from strings to a corresponding numeric value. This process is called vectorisation functions. There are several options for the extraction of features such as One Hot Encoding, Count Vectorizer, N-grams, Hashvectorizer, Term Frequency – Inverse document, etc. . The process of CountVectorizer to tokenise was applied through the following steps

- We imported Countvectorizer from sklearn.feature_extraction.text
- We created a CountVectorizer class instance
- We built vocabulary using the fit() function
- We then transformed each tweet as a vector using the transform() function

The encoded vector has the length that of the entire vocabulary, which is 14,461 features. The CountVectorizer works by performing an integer count of the number of times each word occurs in a tweet, called sparse vectors. It is because each row contains many zeros, an indication of words in the dictionary which are not the tweet. We made use of python's sklearn feature extraction implementation of the CountVectorizer.

Model Training Parameters and Metrics
This subsegment describes the details of machine learning algorithm using in training our emotion detection model and also provides information on the metrics used to determine the performance of our mode.

Stochastic Gradient Descent (SGD Classifier), a machine learning algorithm was used to train the model. It is a simple and efficient method of fitting linear classifier and regressors under convex loss functions. SGD Classifier is efficient and easy to implement. It loops over the randomly shuffled data samples based on the update rule given by equation (1)

$$w \leftarrow w - \eta\left[\alpha\frac{\partial R(w)}{\partial w} + \frac{\partial L(w^T x_i + b, y_i)}{\partial w}\right] \quad \text{equation (1)}$$

Where
η is the learning rate, it controls the step-size in the parameter space. We made use of optimal.
The intercept b is updated but without regularization

The formula foroptimal learning rateis by equation (2)

$$\eta^{(t)} = \frac{1}{\alpha(t_0 + t)} \quad \text{equation (2)}$$

Where t is the time step

$$t = n_{samples} * n\_iter \quad \text{equation (3)}$$

t_0 initial updates equal to size of weights

The dataset used for training process is Mohammad & Kiritchenko, (2018)'s emotion intensity dataset which is already labelled. After the features had been extracted, the labelled dataset was split into 70:30 train test ratio. The training data was made up of 70% (5, 397 tweets) across the four classes while the remaining 30% (600 tweets) was used to determine the performance of the model. SGD Classifier algorithm was used to train the model using the parameters stated in Table 3. The SGD classifier was evaluated based on Accuracy, Precision, F1-Score and Recall metrics. Formulae of these metrics are shown in equations 4 – 7.

Table 3: SGDClassifier parameters

Parameter	Value
alpha	0.001
max_iteration	15
loss	hinge
learning_rate	optimal
random_state	5

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad \text{equation (4)}$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad \text{equation (5)}$$

$$\text{Recall (TP Rate)} = \frac{TP}{TP + FN} \quad \text{equation (6)}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad \text{equation(7)}$$

Where:
TP = True Positive
FP = False Positive
TN = True Negative
FN = False Negative

Results

This section discusses results obtained in the experiments performed. The study is in two phases, the training of the model and using the model to conduct emotional analysis. The experiment was performed on Windows 10 computer with 16GB ram, 1TB Hard drive and intel Core i7-6700HQ CPU @2.60GHz. All programming instructions were written using Python programming language.

Model Training Results

On successfully training the model using 70% of the labelled dataset, the remaining 30% was used to test the ability of the model to correctly determine the emotion expressed in any tweet. The model achieved an accuracy of 92%. The classification report detailed in table 4below, revealed that Joy had the highest recall with 95%, followed by anger with 93%, then sadness with 89% and lastly fear with 0.88%. in terms of F1 score joy had the highest score with 94%, there was a tie between anger and fear with both of them having 92%, and sadness had 88%.

Table 4: Summary of SGDClassifier Report

Classifier	Emotion	Accuracy	Precision	Recall	F1
SGDClassifier	Anger	0.92	0.91	0.93	0.92
	Fear		0.97	0.88	0.92
	Joy		0.93	0.95	0.94
	Sadness		0.88	0.89	0.88

Emotional Analysis of Naija4States LockDown Tweets

The Emotion Detection model EmoDet reported in section 3.1 was applied on the study dataset; each tweet was assigned an emotion label by the EmoDet emotion detection model. As shown in Figure 3 below, a total of 6,681 lockdown tweets are said to be expressing anger. 7,369 tweets expressed fear, 4,492 expressed joy, and 3,925 tweets expressed sadness. Fear is the most predominant emotion across each of the states. Below is the sum total of emotions per emotion category in each state. Distribution of detected emotion chat below reveals that fear is the most dominant emotion across the 4 states examined, accounting for 32.8% of all the Naija4StatesLockDownTweets dataset. Anger was detected in 29.74% of the tweets that made up the dataset, joy had 19.99% while sadness was detected in 17.47% of the overall tweets that made up the dataset.

Figure 3: A combination of Leisure and Psychomotor Activities to choose from during lockdown.

Psychomotor Activities.

These are activities directed at maintaining the psychomotor domain in persons desiring such attribute. They are physical in nature, and at the same time keeps the performer in an exhilarative state of mind in readiness for mental tasks, which demand higher levels of reasoning. For instance, white-water rafting, a water recreational exercise, is described as an especially exhilarative adventure.

It is thus important to find adventure in an adopted psychomotor activity, towards the expected goal. Adventure within the immediate vicinity is important during lockdowns, and as much as the lockdown is relaxed and can afford movements a few kilometers away from home, it is good to seize the opportunity to embark on a few physically challenging activities next to nature. It helps to elevate the mind above the fear invoked by the pandemic, and gives the necessary daring set of mind required to survive the situation. Psychomotor activities include; Water rafting, Solo or Duo canoeing, Forest Hiking, Bush camping, Hill climbing/camping, Lowly organized games maximum of 2 aside, beach volleyball, beach soccer Figs 9 & 10, bowling, mountain biking Fig 14, manual harvesting on farms, hunting expedition, setting traps and picking games from traps Fig 11.

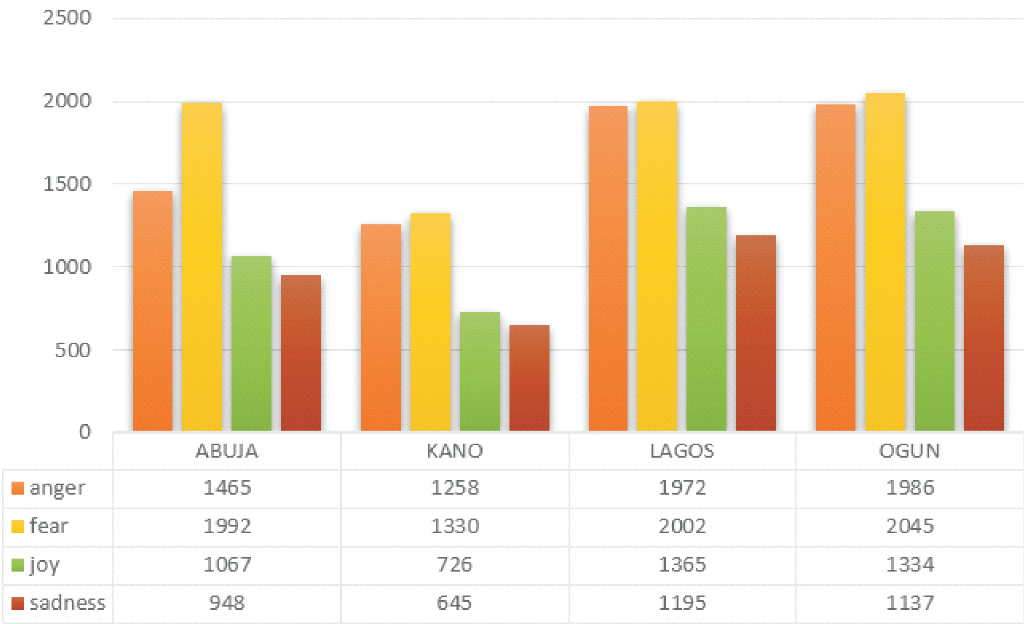

Figure 4: Distribution of detected emotionsper state

In Abuja, 36.40% of the lockdown themed tweets expressed fear, 26.77% expressed anger, 19.50% expressed joy, and 17.32% expressed sadness. In Lagos, 30.64% expressed fear, 30.18% expressed anger, 20.89% expressed joy, while 18.29% expressed sadness about the lockdown. 31.45% expressed fear, 30.54 expressed anger, 20.52% expressed joy and 17.49% expressed sadness in Ogun state originated tweets on lockdown. Finally, in Kano, the trend remained the same with 33.59% of Kano based lockdown tweets that were collected expressing fear, 31.78% expressed anger, joy was evident in 18.34% while 16.29 of the tweets expressed sadness towards the lockdown. Instances of tweets with predicted tweets is shown in Table 5.

Table 5: Sample labelled Tweets in the proposed EmoDet model

TWEET	PREDICTED EMOTION
"The state currently has no active isolation center or testing unit, and you just want to lockdown the commercial activities? That's crazy if you ask me. The funds should be channeled into sensitising the people a bout the COVID-19 than just forcing them to stay home".	anger
"Then one truck driver allegedly ran into one of the electricity poles. So light hasn't been available. I'm just tired. Can this lockdown be over. I'm so looking forward to going to work or at least go out. It feels like an house arrest".	anger
"Mr gov, I salute you Sir. Lock down starts on the 1st of April, but price of garri is 1,500, local rice 30k. what is d hope of d common man in d street ? If is 5k, provice means in which these Cash can genuinely go round to every Deltans sir.. Stay @home for 2 wks isn't a joke".	fear

"Global recession is imminent after the pandemic is over and employees would be one of the major victims as organisations may consider rightsizing. It's important that empl oyees use the lockdown period to acquire skills in order to be more relevant at workplace".	fear
"Market is opened (People that sell food stuff) , even restaurants unless you're living in one of the states that they declared total lock down .Having some money in your bank account itself brings peace of mind".	joy
"I need this lockdown extension... At least for the rest of the month".	joy
"Big bros J, everything us wrong here in abj, on lockdown no cable sub, no data, no food in d house now bag of water i s 150.. See me begging who wants to send me airtime to convert it to cash n send to my aza.. No response till now This coro really show people true colors sha pic.twitter.com/y5XLbWksuq"	sadness
"There's no enforced lockdown in Lagos. I pray this thing do esn't enter any of these crowded slums like Oshodi, Bariga, Ajah. If it does, na till next year. All it takes is for one house help to contract it from their boss. Then Armageddon!"	sadness

Furthermore, we conducted trend analysis of the emotions to determine how the emotions varied from one type of emotion to the other per state. In Abuja as shown in Figure 4 below, at the beginning of lockdown, fear was the most dominant emotion, followed by anger, while sadness and joy were at equilibrium. Much later, there were variations between tweets expressing joy and sadness with each of them becoming more dominant than the other. When it comes to fear and anger, the trend was consistent until towards the last few days of the lockdown, tweets expressing joy became most dominant. This was followed by anger and fear being within the same range, and lastly sadness. Summarily, towards the end of the 15 days, fewer tweets were talking about the lockdown in Abuja.

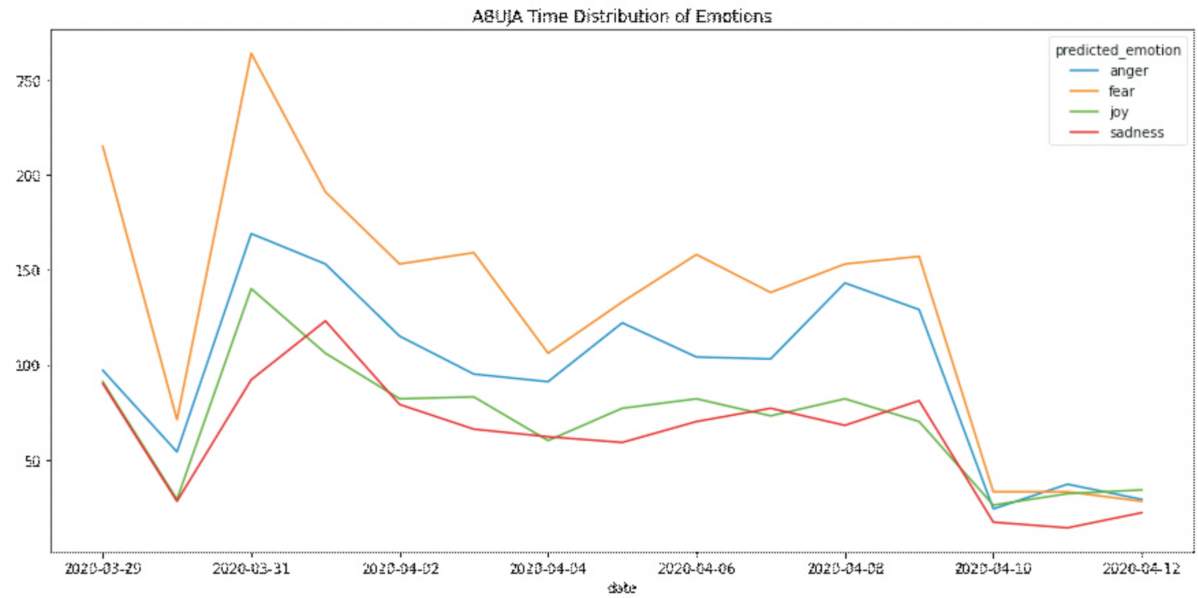

Figure 5: Abuja Time Distribution of detected emotions

In Lagos, as shown in Figure 5, fear was the most dominant emotion in tweets that originated from Lagos state, this followed by anger, joy and then sadness. This trend remained until midway into the lockdown period when the most dominant emotion in the tweets became anger, followed by fear while joy and sadness remained consistent. It remained constant except for a slight rise in the number of tweets expressing sadness in the last days of the lockdown period.

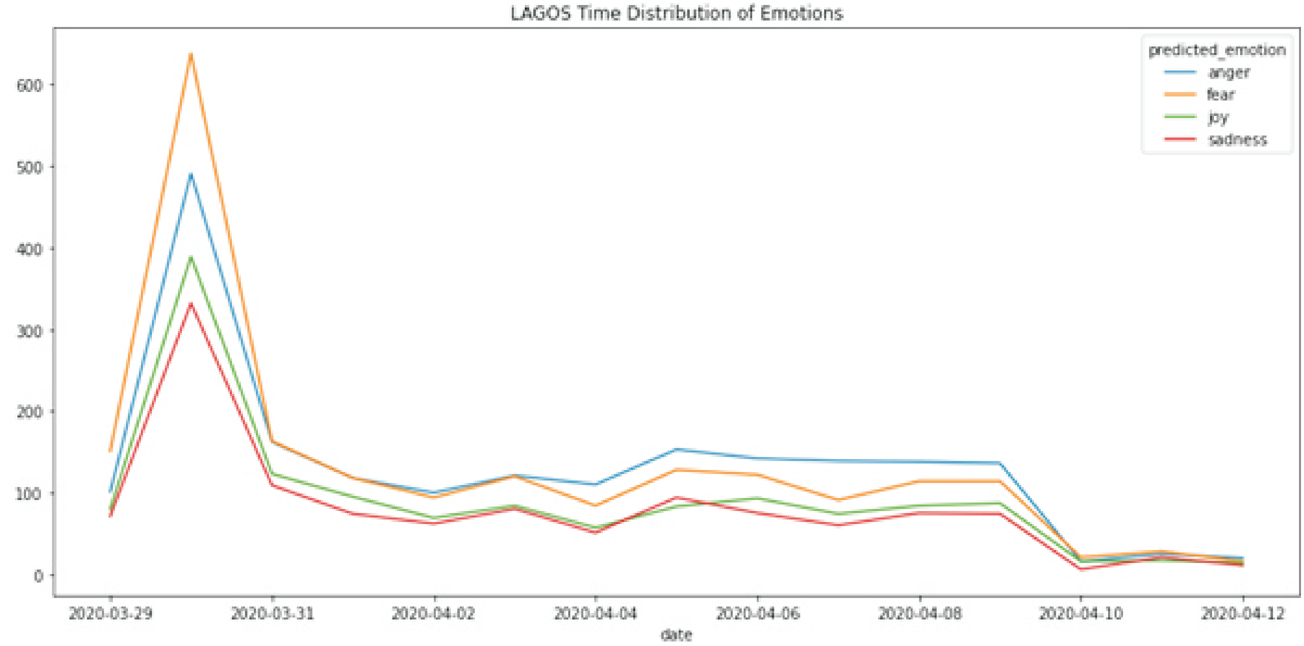

Figure 6: Lagos state Time Distribution of detected emotions

At the beginning of the lockdown exercise in Ogun state, the first prevalent emotion was fear, followed by anger, sadness and lastly joy as revealed by Figure 6. However, within the first quarter, it changed with anger becoming dominant, followed by fear, joy and sadness. Things changed within the second quarter with fear leading, followed by joy, anger followed by sadness. Towards the last few days of the time of the study, the there was an alternate between fear and anger which ended with fear becoming dominant, this was followed by anger, then sadness also surpassed joy in the last days of the study.

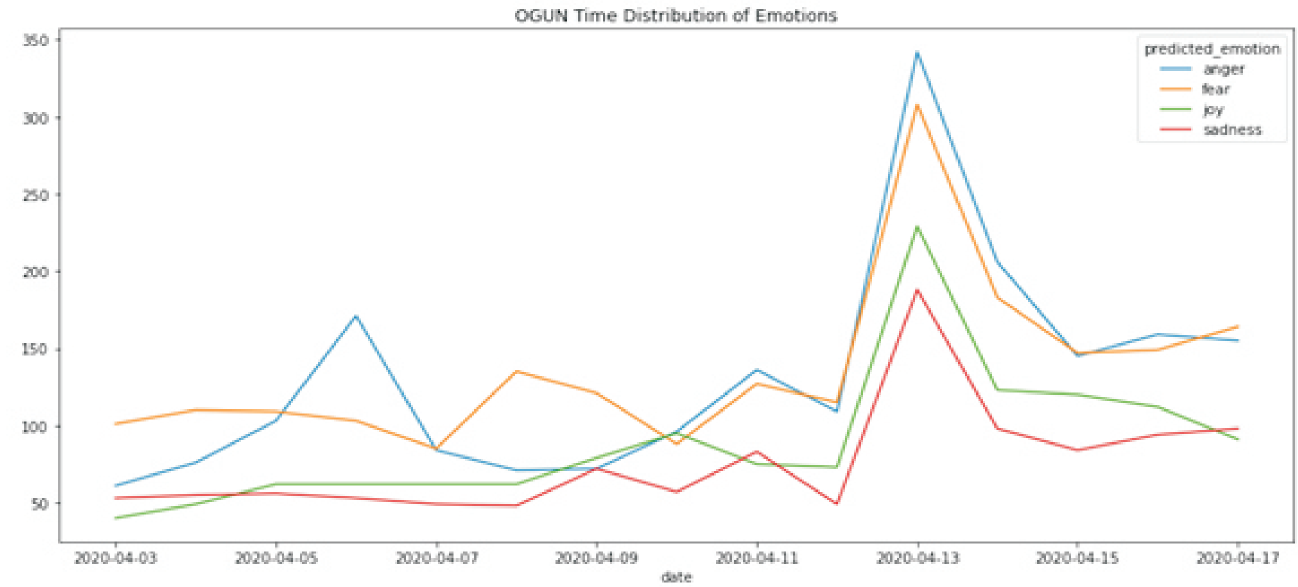

Figure 7 : Ogun state Time Distribution of detected emotions

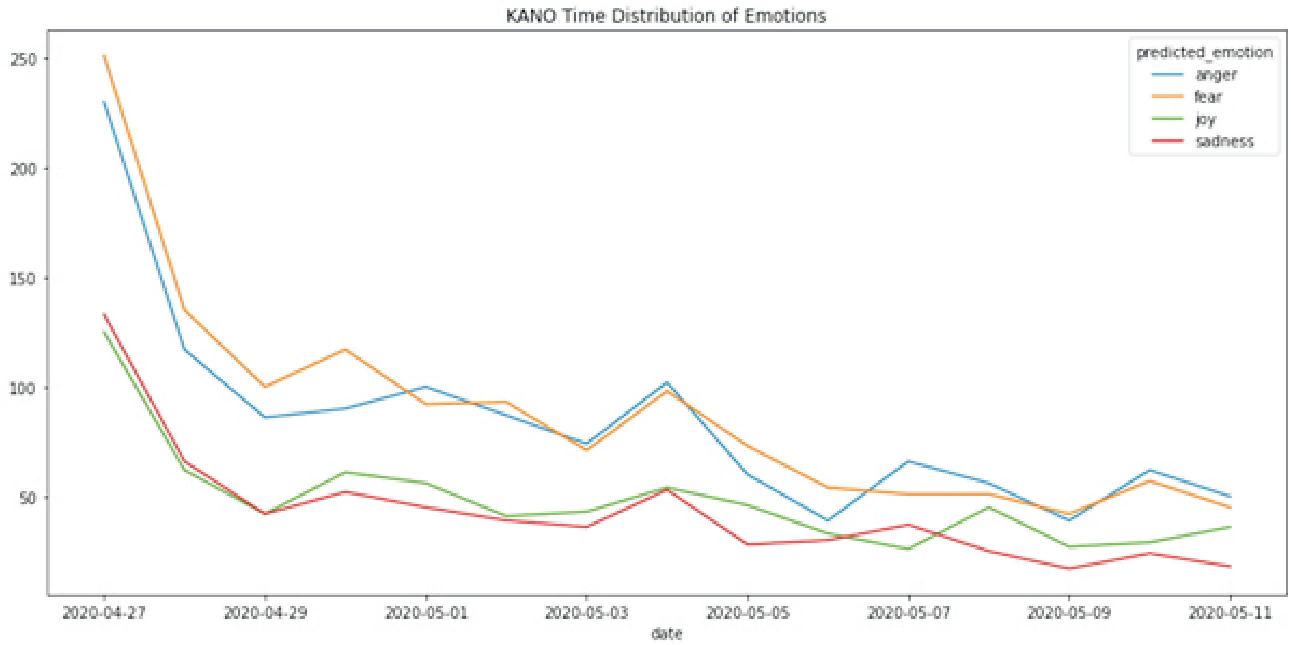

Figure 8 : Kano state time distribution of detected emotions

Figure 7 shows the time distribution of emotions in Kano state. At the beginning of the study, fear was the most dominant, followed by anger, sadness and lastly joy. This trend remained consistent all through the period of study. However, there were alternations between fear and anger with anger being the most dominant emotion as at the end of the study period. The same pattern is manifest in the relationship between joy and sadness. They alternated until but towards the last quarter of the study, joy surpassed sadness.

Conclusion

The study developed an SGDClassifier named EmoDet which was used to classify an already existing emotion labelled dataset. Then, the Naija4StateLockDownTweets dataset fed to the newly build EmoDet model to label and classify according to the labels obtained based on the emotions of residents of Abuja, Lagos, Ogun and Kano states of Nigeria towards the lockdown policy enforced by the government towards reducing the spread of COVID-19 a disease associated with the novel coronavirus. According to (Khair, Yaacob, Hariharan, & Basah, 2012), human activities are related to their emotion, and emotional stress affects human's activities, including behaviour. (Damasio, 1994) further established that emotions are essential in decision making, while (Lašas, 2011) asserts that there is a strong relationship between anger and revolution. The dominance of anger and fear in tweets shared in states where government-enforced lockdown best explains the reason why the lockdown was not effective in Nigeria. The tweets reveal that economic hardship and food insecurity is the major source of the predominant fear and not coronavirus itself this is confirmed in newspaper reports such as (AFP, 2020; mynigeria.com, 2020). Also extracted tweets reveal that lack of infrastructure is the source of the anger. It is recommended while the source of sadness includes fear on lack of food since they could not work. Government needs to ensure that infrastructure is put in place to ensure social welfare of its citizen during lockdown as it is obvious that out of fear of dying of hunger, people breached the lockdown in search of food and other basic amenities that could have been provided by the government.

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