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Sentiment analysis of the NIGERIAN nationwide lockdown due to COVID19 outbreak

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Abstract
Sentiment analysis is a classification technique that specializes in categorizing a body of texts into various emotions. This categorization had proven to be handy in classifying tweets into positive, negative, or neutral emotions. Nigerians had been on a nationwide lockdown due to COVID19 since 30th March 2020. The analysis of the emotions of Nigerians during this period is expedient to understand the effectiveness of exercise and the impact it has on the masses. The focus of this paper is to determine the sentiment analysis of Nigerians within the period of the lockdown exercise. Using a lexicon-based analytic architecture and a streaming API to TwitterNG, we extracted a total of 22, 249 tweets from the timelines of national stakeholders on COVID19 and location-based tweets from the general public. The tweets were extracted and collated using a set of ten hashtags/keywords from 30th March to 11th May 2020. The analysis was done in R Programming Software with the application of the NRC lexicon approach to classifying the emotions of Nigerians within the period. The result showed that Nigerians expressed an overall positive sentiment to the lockdown exercise despite a few negative expressions.

Keywords: Coronavirus, COVID19, lockdown, twitter sentiment, sentiment analysis

1. Introduction

Millions of Nigerians are connected online and they make active use of the social media networks especially Twitter, a microblogging platform with over 330 million daily users. Twitter has served as a free platform where users express their opinions over any event. Both personal and corporate opinions on critical disasters and outbreaks like floods (Meera, *et al*., 2017) [16], ebola (Hossain *et al*., 2016), and zika (Mamidi *et al*., 2019) [15] had been shared on Twitter. As a social platform that collects global opinions over events, Twitter is currently playing the same role in the 2019 Coronavirus Disease (COVID19) outbreak caused by the novel SARS-Cov-2 virus. Although the outbreak started from Wuhan, China in December 2019, it has spread all over the world through its human to the human mode of transmission causing the World Health Organization (WHO) to declare it a public health emergency of international concern in January 2020 (WHO, 2020a) [29] and a global pandemic in March 2020 (WHO, 2020b) [30]. The number of confirmed cases increases daily resulting in a casualty of 282, 244 deaths globally as in the middle of May 2020 (ECDC, 2020) [5]. Following the epidemiological trends and recommendations from medical personnel, many countries of the world resorted to a complete national lockdown as a way to contain the spread.

Nigeria announced her national lockdown in phases. The first phase locked down the two (2) major states where the outbreaks were first reported and the federal capital territory for an initial period of two (2) weeks. The second phase consolidated the first phase for another two (2) weeks while all other states locked down her activities against any gathering of people. The third phase locked down states' borders to halt interstate travels and started a gradual easing or sectorial reopening of the initial two (2) major states and the federal capital territory while enforcing rules of social distancing and wearing of face masks. Despite these lockdown measures, the COVID19 cases in Nigeria were on the rise as 4399 confirmed cases were reported in the middle of May 2020 (NCDC, 2020) [14]. As expected, Nigerians took to the social network to express their opinions over the events. This work aims to mine these opinions and using topic modeling, assess the feelings of the populace during the lockdown period.

The assessment of people's feelings in a body of texts is referred to as sentiment analysis. It is the application of natural language processing methods in determining the subjective information in a body of text (Vishal and Sonawane, 2016) [27]. Over the years, there has been an increased wave of interest in this area due to the growth in the use of social media to reflect opinions and feelings (Pang and Lee, 2008) [20].

Different approaches had been employed in sentiment analysis research. Table 1 shows the general-purpose sentiment lexicons.

Table 1: Publicly available general-purpose sentiment lexicons in the English language

Lexica	Description	Reference	Mode of Compilation
MPQA	8000 words annotated with positive, negative, and neutral polarities	Wilson *et al.* (2005) [28]	Manually compiled unigrams
Liu's opinion lexicon	6800 words categorized into positive and negative	Hu and Liu (2004) [13]	
AFinn lexicon	2500 words rated between -5 to 5 polarities	Hansen *et al.* (2011) [8]	
NRC lexicon	54,129 unigrams, 316,531 bigrams and 480,010 skip bigrams extracted from tweet collection	Mohammad *et al.* (2013) [17]	Automatically compiled N-grams
Geri lexicons	376,863 unigrams, 922,773 bigrams and 850,074 dependency triples	Ozdemir and Bergler (2015) [19]	

Adapted from Ogbuju and Onyesolu, 2019 [18]

Most of the approaches use the general-purpose lexicons to extract the feelings of the texts in any situation. For example, the Liu's lexicons had been used in Ogbuju *et al.* (2017), the NRC lexicons in (Dubey, 2020) [4], the Afinn lexicons in (Lohiya, 2018) [12], the MPQA lexicon in (Wilson *et al*., 2005) [28], and the Geri lexicons in (Ozdemir and Bergler, 2015) [19].

This research took into account the tweet from Twitter NG which is the informal name for Nigeria Twitter users. We gathered the tweets for a period of six weeks from 30th March to 11th May 2020 using filters to determine their relationship with the COVID19 lockdown. Our result will show how Nigerian citizens coped with the lockdown as well as present the various emotions felt by different people during the period.

2. Review of Related Works

Considering that Twitter as a social media tool has a lot of important features for data mining, Daniel (2015) [3], analyzed the concept of Twitter mining. He pointed out features such as hashtag, date of tweets amongst others available for data mining on Twitter. He elaborated on the analysis of semantic contents on tweets such as Sentiment Analysis as part of Twitter mining. The author also revealed that Twitter mining has aided some discoveries and predictions in various areas like political elections, the national economy, and the spread of diseases. Elaine (2015) [6] demonstrated how Brownstein, a web epidemiologist used Twitter data to track cholera and to determine the side-effects of drugs using a platform that could listen to tweets on Twitter and predict an outbreak of food poisoning. The real-time and global coverage attribute of Twitter makes it better than the time consuming traditional methods of gathering and sourcing for data in epidemiological research. This study established the fact that Twitter data will have a lot of impacts whenever a global pandemic would happen.

Sophie *et al.* (2018) reviewed how twitter data have been mined and analyzed for public health applications. These applications include monitoring diseases, public reaction, and lifestyle. In these reviews, classification, labeling, and other methods were applied to extract meaningful information. Machine learning techniques such as Random Forest and Support Vector Machine were also applied to the tweets proving that machine learning techniques can be fully utilized to extract meaningful information from tweets. A clear proof of this was a work by Baker *et al.* (2020) [2] which studied epidemic diseases using sentiment analysis and proposed a novel approach that detects Influenza disease epidemics in sixteen (16) Arab Countries, using community tweets in Arabic common language. A vast amount of tweets were collected from different Arab countries, classified, analyzed, and processed using Naive Bayes, Support Vector Machines, Decision Trees, and K-Nearest Neighbor to measure the quality and performance of the proposed approach. The result showed that the citizens can actively help in fighting the influence of any epidemics such as influenza before they possibly occur in the neighboring countries.

In the same vein, the UN Global Pulse (2014) [26] mined Indonesian tweets to understand the crises in food and fuel price. Phrases relevant to food and fuel prices were formulated in Indonesian local Bahasa language to get the required contents from Twitter. They trained the classification algorithm to analyses the sentiment of the related food prices using Crimso Hexagon's AI-based automated monitoring software (Track brand mentions and Sentiment Analyzer). The tweets extracted are categorized into four basic groups (Positive, Negative, Confused, and Neutral). Time series analysis was used in quantifying the correlation between food and fuel-related tweets and official food inflation statistics. Their research showed a correlation between the two topics which means that an increase in price affects food and fuel security. Other works like Fung *et al.* (2012) [7] and Patel *et al.* (2015) [21] validates that social media platforms can be used to uncover people's reactions related to food and fuel issues. The classification of sentiments as a machine learning technique had been applied in Adhikari *et al.* (2018) [1] which did work for epidemic prediction using five (5) sentiment classifiers (long-short term memory, recurrent neural network, frequency inverse-document frequency, deep neural network, and autoregressive integrated moving average). This was done with the support of different feature extraction techniques to predict commonly occurring diseases in a particular area. The work aimed at detecting the outbreak of the epidemics using tweets that are a country based extracted with the name of the epidemic using the Twitter API. Pollacci *et al.* (2017) [23] applied a Support Vector Machine algorithm on a model for lexicon-based sentiment analysis on Twitter data and validated over an extended dictionary for prediction of outbreaks.

Another work in this line was by Mamidi *et al*. (2019) [15] which provided insights concerning the 2015 – 2016 Zika epidemic by identifying key topics bearing negative sentiment on Twitter. The research was conducted to study public sentiment concerning the Zika Virus and analyzed the negative effect of the virus using social media platforms with a focus to determine the qualitative characteristics of the positive, negative, or neutral thoughts expressed. Using machine learning algorithms and techniques, a total of 5030 tweets were extracted with explanatory comments to train multiple classifiers with word2vec and n-gram models while keeping the focus on the negativity of the virus. Their study enabled public health officials to understand public sentiment regarding the widespread of the virus and helped them to address specific elements of the various sentiments in real-time. Apart from Twitter, all social media platforms can be mined. The work by Hossain *et al*. (2016) demonstrated the usefulness of mining social media platforms to inform public health education. It systematically collected data on the Ebola outbreak for a period of 31 weeks from online databases such as ProQuest Newsstand, Dow Jones Factiva, Program for Monitoring Emerging Diseases (ProMED) as well as Google. The work advocated the use of social media as an alternative information network to complement the traditional, filed, and work-based surveillance approach.

The study on epidemics predictions using machine learning has helped to provide efficient ways to restrict epidemics from spreading. It has equally improved the survival rate, recovering rate, and reduced the death rate. This was demonstrated in Singh *et al*. (2018) which applied machine learning techniques on sentimental analysis to predict any sudden outbreaks and epidemics with datasets from Twitter. The research helped in detecting the dengue outbreak at an early stage. It is a popular belief that prevention is better than cure. It is in the light of this that following the incessant spread of epidemic diseases across the globe, Ji *et al* (2013) [9] explored the potentials of providing monitoring for public health personnel using machine learning-based Twitter sentiment classification. They developed an Epidemic Sentiment Monitoring System which helped public health officials to keep track of spreading epidemics, its location, and the rate at which it spreads through measuring the degree of concern of the Twitter users in real-time.

In another study which focused on the current coronavirus global pandemic, Peng *et al*. (2020) [22] built a modified Susceptible Infected and Recovered (SIR) model from the classic SIR model by introducing a "proportion of the infected that is not effectively isolated from the susceptible at a given time point". Apart from the study's validation of the effectiveness of the city lockdown and intensive community screening approaches in China, it also predicted an exponential increase of infection cases in Italy and South Korea if the city lockdown and intensive community screening approaches are not followed. Still, on the coronavirus pandemic, Dubey (2020) [4] used the NRC lexicons to study the sentiments of citizens of twelve countries during the COVID19 pandemic. He found that countries like Belgium, India, and Australia are majorly expressing positive and hopeful sentiments about the pandemic while others like China, France, Switzerland, Netherland, and the USA expressed negative, distrust, and anger sentiments on the same.

In summary, we have evaluated works of literature which had shown that data mining techniques can be used to extract and generate results that can have a significant impact in decision making especially in the onset of an epidemic or a pandemic. Specifically, our review of related works had shown the use of Twitter data in the fight against epidemics using various techniques. However, very little works had shown the application of the emotional classification of tweets during an epidemic. Although recent works like Dubey (2020) [4] and Barkur (2020) [2] had attempted solutions in this premise in different countries, the holistic architecture advocated in this work had not been followed. Also, none had been done in the context of Nigeria. It is in the light of this gap that this work sets to extract and collate tweets from both government stakeholders and individual channels for a comprehensive study of not just the public opinions but the reactions of the public to the different measures put in place for the fight against the COVID19 pandemic.

3. Materials and Methods

The materials used in this work are extracted from three (3) sources. First, the exploratory dataset that provided public opinion insights into the pandemic was collected from the IEEE-Dataport (Lamsal, 2020a) [29]. The data port has tweets that were fed by a model that monitored the real-time Twitter feed for coronavirus-related tweets from 20 March – 10 May 2020. Second, the first-level analysis was done using location-based tweets from Nigeria starting from the first phase of the lockdown exercise. The tweets were filtered with the following 10 keywords: "corona", "coronavirus", "COVID", "covid19", "isolation", "lockdown", "quarantine", "stayhome", "staysafe" and "nigeria". Third, the second-level analysis was done using tweets from the timelines/handles of relevant Nigerian stakeholders in the fight against COVID19. These stakeholders include the COVID19 Presidential Task Force (@DigiCommsNG), the Federal Ministry of Health (@Fmohnigeria), and the Nigeria Centre for Disease Control (@NCDCgov).

Table 2 shows the overall statistic of the dataset.

Table 2: Dataset Statistics

Data Sources	No of Datasets for Analysis	No of Datasets for EDA
Dataport Tweets	N/A	76, 931, 831
Location-based tweets	21, 211	21, 211
Nigeria Presidential Task Force on COVID19	163	N/A
Federal Ministry of Health, Nigeria	113	N/A
Nigeria Centre for Disease Control	762	N/A
Total	22, 249	

The text analytic architecture used in the overall workflow is shown in Figure 1.

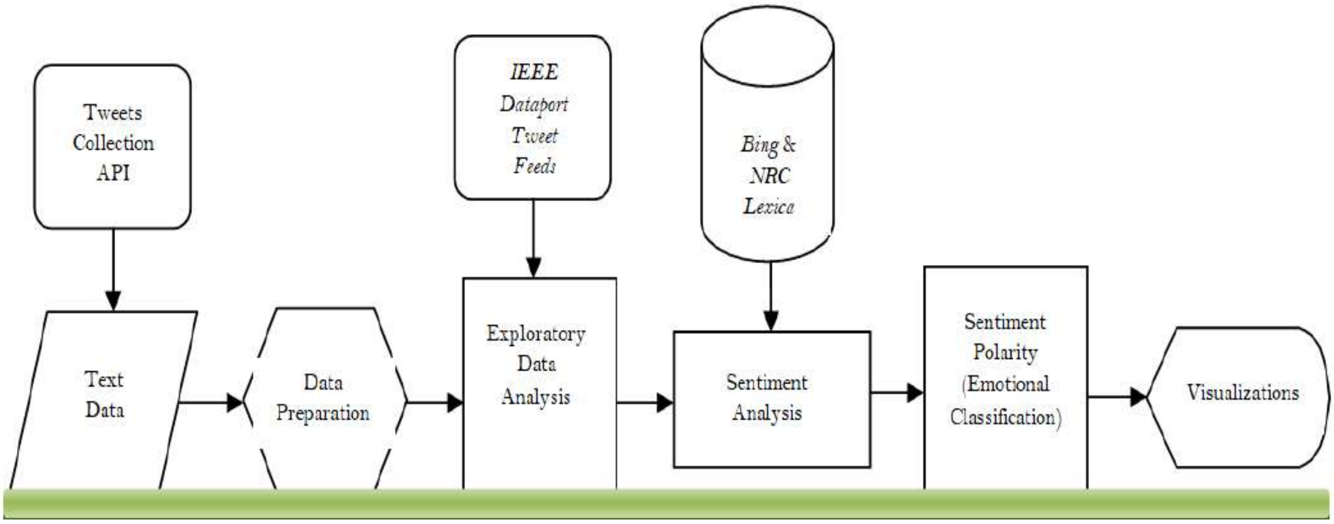

Fig 1: Analytic Architecture

The datasets were collected using a Twitter API handshake with the R Programming. Figure 2 shows a screenshot of the dataset.

	text	favorited	favoriteCount	replyToSN	created	truncated	replyToSID
1	RT @SilverbirdTV: Alleged new sitting arrangement in Lagos...	FALSE	0	NA	2020-05-10 21:46:56	FALSE	NA
2	Clay Richie: Governance and politics: the Ni		0	NA	2020-05-10 16:01:59	TRUE	NA
3	RT @FutureInvestFX: @McStLuke #coronav		0	NA	2020-05-10 13:35:02	FALSE	NA
4	@McStLuke #coronavirus #COVID19 #Stay/		0	McStLuke	2020-05-10 13:24:10	TRUE	1259412332050026
5	RT @bbcnewspidgin: Join us dis Sunday as		0	NA	2020-05-10 11:54:59	FALSE	NA
6	Nigeria is on auto pilot, My prayer is we land safely. The que...	FALSE	0	NA	2020-05-10 09:21:37	TRUE	NA
7	Join us dis Sunday as we go dey tok live with larrygaaga ont...	FALSE	1	NA	2020-05-10 09:11:44	TRUE	NA
8	My love for this song! #2Wrongs #TwoWrongs #wyclefjean ...	FALSE	0	NA	2020-05-09 21:35:18	TRUE	NA
9	Lockdown na for who get house. #COVID19 #Covid_19 #co...	FALSE	0	NA	2020-05-09 18:57:05	FALSE	NA
0	New Followers: 386 Total Followers: 3912 New Unfollowers: ...	FALSE	0	NA	2020-05-09 17:33:47	TRUE	NA

Fig 2: Screenshot of Dataset

Though the dataset had 16 columns, only the text column is relevant for the analysis operations hence it was selected and pre-processed through tokenization, stop words removal, stemming, and creating a term-document matrix/ngram. The NRC Lexicon approach (Mohammad & Turney, 2013) [17] was used to express the sentiments into eight (8) emotions.

4. Results and Discussion

This work validated the fact that there is a rise in the global interest in COVID19. This was achieved through the exploratory data analysis of the IEEE-Dataport which showed a global increase and decrease of COVID tweets from 20 March but a striking increase from 18 April (see Figure 3). This shows a rise in global interest as individuals and stakeholders are constantly tweeting about the pandemic well over 2 million tweets per day.

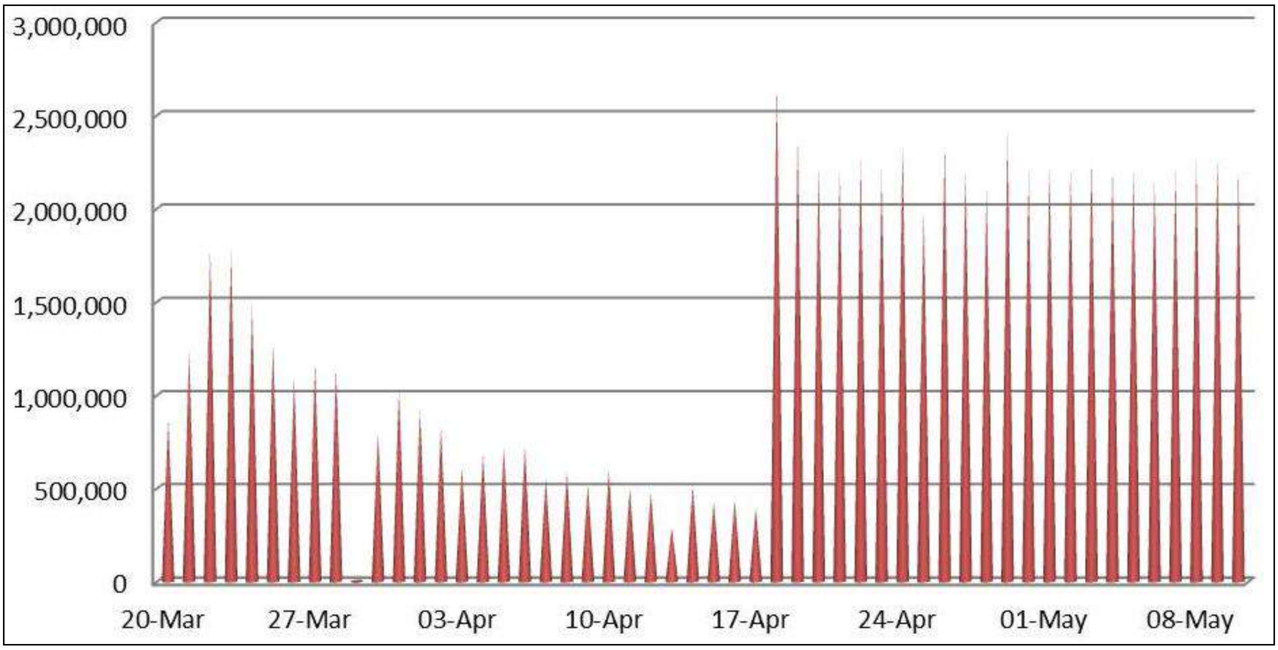

Fig 3: A rise in global interest in COVID

The location-based tweets and the tweets from the relevant COVID19 stakeholders in Nigeria were combined for the lockdown analysis tasks. First, the result shows that the top favorited tweets are those that (i) announce the confirmation of new cases, (ii) praises the inclusion of new laboratories in Lagos and Ogun, and (iii) expresses the dedication of health personnel or shows that health workers are in the frontline of COVID19 response across Nigeria. Secondly, the result shows that the topmost retweeted messages are those that (i) promote the use of facemasks, social distancing and handwashing practices, (ii) advocate the closure of airports and restriction of movements/interstate travels, and (iii) announce the confirmation of new cases. The least retweeted messages are those that announce the government administrative or processes in the fight against COVID. The unpopularity of these tweets shows that Nigerians were most interested in real actions or solutions and less interested in the bureaucratic processes for the solution. Thirdly, the most frequent words used in all the tweets are lockdown, COVID, and Lagos. This is also shown in the word cloud in Figure 4.

Fig 4: Word cloud of COVID lockdown in Nigeria

The result of the analysis of the lockdown tweets using the NRC lexicon is presented in Figure 5.

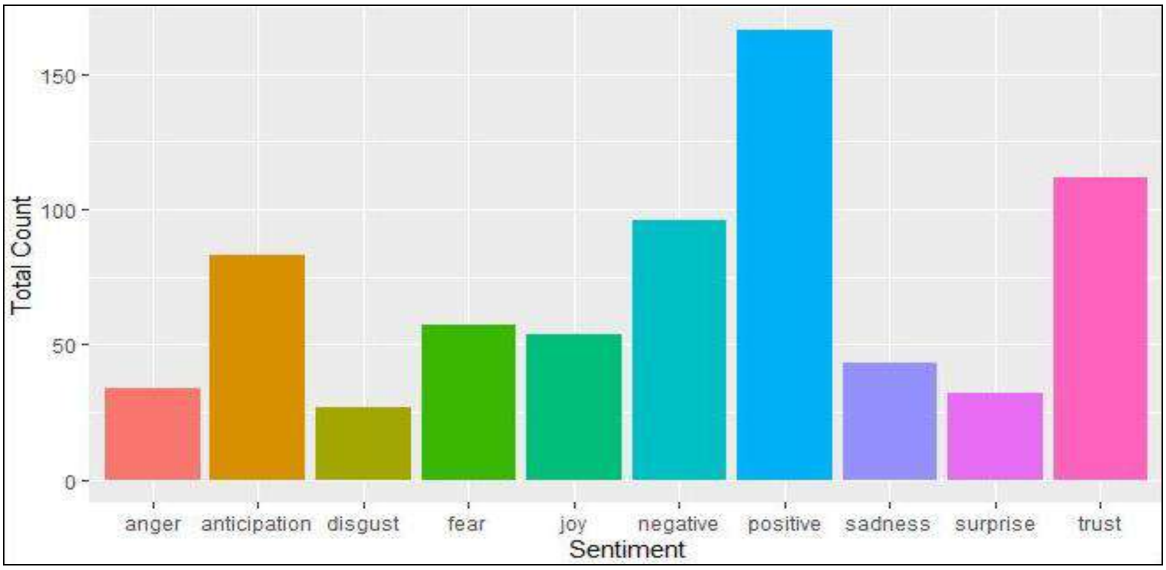

Fig 5: Emotional classification of lockdown tweets in Nigeria

It shows a low expression of negative emotions like anger disgust, fear, and sadness. The expression of positive emotions like anticipation (hope), joy, and trust are high thereby giving an overall high positive sentiment.

There were few expressions of surprise which arise as a result of the imposition of the containment measures to all citizens irrespective of culture or religion as all traditional ceremonies and religious activities were halted by the lockdown. The swift implementation of the lockdown also came as a surprise to some Nigerians while others expressed sadness over the harsh treatment of the citizens by the law enforcement agents against the lockdown defaulters. Also, the surprise expression shows that no palliatives were provided to cushion the economic effects of the lockdown, especially on low-income families. Also, it was surprising to Nigerians to read about the sharing of palliatives donated by spirited individuals to only a section of the Country.

The expressions of anger and disgust arise from the ineffectiveness of the self-isolation practice. Nigerians did not expect the self-isolation practice to be an advisory measure. It should have been a compulsory measure implemented by the government on all passengers who flew into the country. Other sources of the disgust emotion came from tweets expressing displeasure on the alleged passing of the NCDC epidemic bill by the Nigerian Senate during the lockdown.

Generally, the result shows that Nigerians are in support of all spirited government efforts to contain the virus and stop the community spread. They have shown an overall positive emotion to the lockdown measure. Comparing this result with the global sentiments of COVID tweets presented in Figure 6 (40.7% positive against 20.7% negative), one would discover the accuracy of the result as it becomes clear that all countries globally accepted the lockdown measures in good fate and are positive with the fight against COVID19.

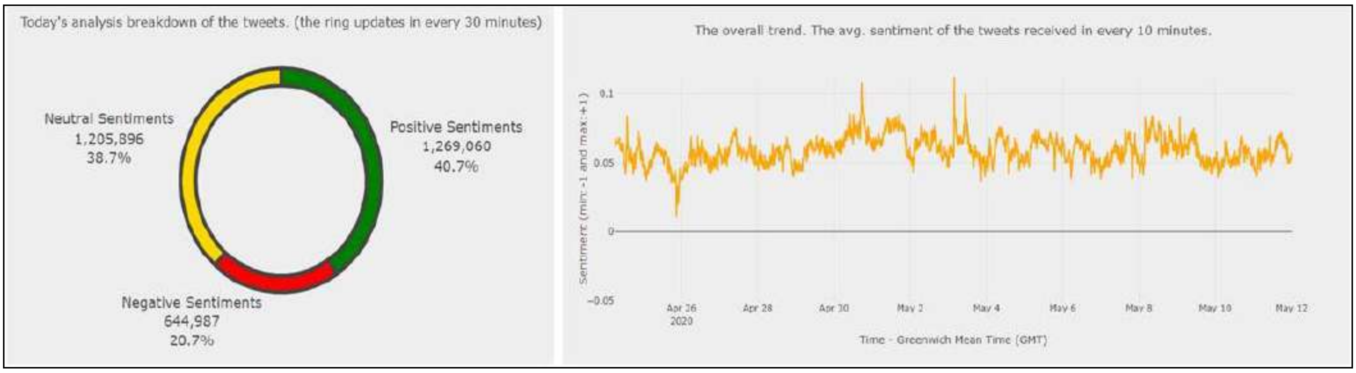

Fig 6: Global sentiment of COVID tweets. Source: (Lamsal, 2020b) [30]

The work of Lamsal (2020b) [11], Peng *et al*. (2020) [22], Barkur (2020) [2], and Dubey (2020) [4] all reported an overall positive sentiment on the nationwide lockdown due to COVID19. This shows that the lockdown exercise, though with some economic effects on the nations, was an acceptable control measure in the fight against the pandemic.

5. Conclusion and Recommendations

In this work, we have aggregated and analyzed a set of tweets by users geo-tagged as Nigerian during the period of COVID19 lockdown and mined the emotions displayed based on the sentiments in the tweets. We used the state of the art NRC lexicon approach to classifying the feelings of the Nigerians in eight (8) basic emotions during the period.

Despite the few negative emotions expressed, our overall result showed that Nigerians expressed a positive sentiment about the lockdown exercise and were supportive of all government measures to contain the pandemic. We recommend that relevant stakeholders in Nigeria should make use of the sentiments discussed in this work to reduce or eliminate the concerns which amounted to the negative sentiments. As a limitation/future work, we acknowledge that we used tweets in the English language which is the official language in Nigeria but there were presences of tweets in the Nigerian-Pidgin which we could not properly analyze due to the absence of publicly available sentiment lexicons in the Nigerian-Pidgin. In the future, we hope to mine the opinions and reactions of Nigerians in a post-lockdown scenario and compare it with the current research while also taking into account the presence of tweets in the Nigerian-Pidgin.

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