Journal of Applied Artificial Intelligence
https://jaai.sabapub.com
ISSN: 2709-5908

2022 Volume 3, Issue 2 : 13 – 23
DOI : https://doi.org/10.48185/jaai.v3i2.560

The Sentiment Analysis of EndSARS Protest in Nigeria

Emeka Ogbuju[1, *], Ikechukwu Mpama[2], Temitope Martha Oluwafemi[3], Fati Oiza Ochepa[4], Joshua Agbogun[5], Victoria Yemi-Peters[6], Folusho O. Owoeye[7], Mercy Idoko[8], Bello Taoheed[9]

[1,3,4,6] Computer Science, Faculty of Science, Federal University, Lokoja, 260101, Nigeria
[2] Monitoring and Evaluation, ACF, Initiative For Grassroots Advancement in Nigeria, Lokoja, 260101, Nigeria,
[5] Department of Computer Science, Faculty of Science, Godfrey Okoye University, Enugu 400105, Nigeria
[7] Department of Computer Science, Kogi State Polytechnic, Lokoja 26000, Nigeria
[8] Kogi State University, Anyigba 272102, Nigeria
[9] Guaranty Trust Bank Plc, Lokoja 260101, Nigeria

Received: 10.10.2022 • Accepted: 01.11.2022 • Published: 30.12.2022 • Final Version: 31.12.2022

Abstract: The extraction of public opinions from online communication platforms can serve several purposes in corporate institutions, state politics, and governance. The analysis of these opinions may be useful for both immediate business decision making and professional planning. This analysis is becoming relevant in managing social movements and digital activism by applying computational technology. There is a need to deploy this opinion mining technology to the recent largest digital activism in Nigeria known as the #EndSARS movement. In this work, we proposed the EndSARS live analytics framework which holds a promising solution to social unrest and may serve as a panacea to curbing the menace of vandalism resulting from unresolved protest issues. Using a dataset of 12,357 tweets, we demonstrated that computational technology can be relevant to addressing online protests. The result of the analysis shows the eight basic emotions expressed during the protest and approaches the government may adopt to address future activisms.

Keywords: Digital Activism, Twitter, Sentiment Analysis, Hashtag, Tweets.

1. Introduction

Since the creation of the Twitter microblogging platform in 2006, it had employed its instant messaging capabilities to create tweet posts for both personal information dissemination and social transformation campaigns. As short as 280 characters per post, the tweets can communicate the user's message with a facility to enable a retweet of the message by the messenger's followers. The addition of the hashtag feature (prefixed with the special character '#') to a keyword in the message makes it more coordinated to track chains of messages from different users addressing a particular theme. This feature had given tweets the power for digital activism and social transformation in recent times. The hashtags, which started on Twitter in 2009 [3] were the commencement of what was known as the 'Twitter Revolution' [2] following the online protests against election irregularities in Iran. In line with this, Yang [16] defined hashtag activism as a ‘discursive protest on social media organized with a hashtagged word, phrase, or sentence’. This sort of activism has become the new normal as it affords mostly young people, who are active users of social media, the opportunity to amplify their ideas, raise concerns about hurting issues, and demand justice against social vices.

[*] Corresponding Author: emeka.ogbuju@fulokoja.edu.ng

Hashtags like #Sandiegofire, #OccupyWallStreet, #BlackLivesMatter, and others had trended on social media to address their pertinent issues at various times. In Nigeria, Oloyede and Elega [12] had examined the timelines of the prominent hashtags like #LightUpNigeria which trended in 2009 to express dissatisfaction over poor electric power supply, #EnoughisEnough which demanded a free and fair election in 2011, #OccupyNigeria which challenged subsidy removal on the premium motor spirit in 2012, #BringBackOurGirls which created awareness on the abducted Chibok girls in 2014, #StopBokoHaram which trended against the dreaded terrorist group in 2015, and #FreeLeahSharibu which demanded the release of an adducted young girl on religious matters in 2018. When a unit of the Nigerian Police, known as Special Anti-Robbery Squad (SARS) became notorious for bribes and brutalities against innocent Nigerians especially the youths, the application of the #EndSARS hashtag activism was handy to curb the menace. Although the #EndSARS protest started in 2017 and #PoliceReform in 2018, they took the center stage in 2020 in a mega online protest which later came offline into the streets to demand the end of general police brutalities including extra-judicial killings, physical assaults, extortions, unlawful arrests, and illegal detentions. The protests initially yielded a good result following the proscription of the notorious SARS unit by the Nigerian government and instituting a judicial panel of inquiries in the states. However, when new demands like #End SWAT, #endbadgovernance, and #endcorruption were not addressed satisfactorily, it metamorphosed into a bad dynamic leading away from peaceful street protests into attacks on government properties, police personnel, and vandalization of government-owned palliative storehouses which were believed to be hoarding COVID19 lockdown relief goods.

Our goal in this work is to analyze tweets with the EndSARS hashtag to extract the feelings of the protesters and provide technical advice to the government using the emotions embedded in the messages. This is possible through the application of stream analytics, text mining, and sentiment analysis. Analyzing the sentiments or opinions of tweets had been an active research area in computational sciences in this era of big data analytics. Sentiment analysis extracts the opinions and/or feelings expressed in the body of the text. It had been applied in Ogbuju et. al [10] to mine the opinions of Nigerians about two political personalities by setting up a centralized real-time data collection framework. Also, Ogbuju et. al [11] determined the public opinion of the Nigerian police force and the Nigerian army using datasets collected from their social media accounts with the help of an e-government big data-driven framework. In the same vein, Oyebode and Orji [13] applied sentiment analysis to analyze public opinions during the 2019 Nigeria presidential election to determine who would win the election using social media comments. The application of sentiment classification techniques can be very useful in digital activism. In essence, the purpose for this work in the domain of digital activism with hashtags is to show that with a relevant technology framework and without a physical engagement with aggrieved protesters, the actual opinions of the masses can be collectively collated in real-time, and communicated to the government for informed actions. The usage of frameworks like this will ensure that peaceful protests will not degenerate into a public menace and subsequent destruction of public properties because the concerns of the protesters can be addressed swiftly as they come.

1.1. Review of Related Works

Some works have demonstrated that social media, especially Twitter, can be used by collective action groups to communicate with political office holders, influence political decisions, address issues of social injustice as well as sensitize, educate and disseminate information. For example, in the time of COVID19 in South Africa, Magade [6] examined the emergence of young voices and alternative communication practices for socio-political change by analyzing hashtags, comment threads, and re-tweets of *O Jewa Ke Eng?* (translated *"What is bothering you"*), #COVID19SA and #LockdownSA using network analysis, sentiment analysis, text mining, and content analysis. Morselli et al [9] likewise revealed that opinions on social media such as Twitter can influence street protests, government decisions, and policies. Using correspondence analysis and hierarchical clustering, they analyzed a total of 64,923 tweets from #ConstituteEsMuerte and #ConstituyenteEsVida hashtags of the anti-regime Venezuelan protests in 2017 to discover how opinions changed during the protest with the help of sentiment analysis to extract relevant topics from the tweets, and structural change analysis to track the change in opinion. Furthermore, a study by Tremayne [15] examined the intersection of social movement and social media to see how the concepts of scale shift, collective identity, and framing can be clarified through the use of network analysis. The study used a total of 4995 #OccupyWallStreet tweets between 14th to 31st July 2011 to compute the measures of network centrality with NodeXL and identified the major players of the discourse at the earliest stage. It also showed how the online movement was driven by the scale shift and the sub mechanisms of diffusion and brokerage that occurred simultaneously as well as how to frame bridging and amplification were already evident months before the demonstration began.

In a view to studying the role of social media during social movements that develop online, Brünker et. al [1] applied social network analysis methods to identify the participation of influential users during the #metoo debate. Tweets that pertain to the hashtag were collected and examined between September 30 2017 to November 30, 2017. The examination showed that 1,271 tweets were found as distinct communication while 200 were influential users. The content analysis of the influential users shows that the messages they passed were profoundly related to the issue of sexual harassment, calling for attention and action. Another work that demonstrated the application of hashtags in public issues was done by Sharma et. al [14] using a total of 1,164 #WaterCrisis tweets to gauge the public sentiment around water shortage across the world. The work presented a live tweets framework of a web-based application to visualize the current sentiments associated with the hashtag and plots the results on a map. The primary motivation behind building the application was to provide a single automated platform that serves as a complete end-to-end system for sentiment analysis of Twitter messages along with their visualization. A similar system was built by Zavattaro et. al [17] to analyze a total of 4,779 tweets from 125 cities of the US local government to ascertain if sentiments can positively affect citizen's involvement with the government on social media. The analysis showed 41% as positive tweets, 49% as neutral tweets, and 10% as negative tweets. It was concluded that positive tweets from the local government encourage the involvement or participation of citizens than neutral or negative tweets.

In 2019, Matsilele et al [22] examined the use and effectiveness of social media as a means of expressing dissidence in Zimbabwe. The study collected data from both Facebook and Twitter on four major case studies on dissidence namely, Baba Jukwa, #ThisFlag, @ProfJMMoyo, and #Tajamuka. The study utilized qualitative data analysis and collected data using netnography/virtual ethnography. It concluded that the pattern of dissidence is gradually evolving with the advent of social media providing a rich platform for expressing dissatisfaction with the status quo.

The ability of social media interactions to accurately capture and represent the sentiments of society at large and subsequently serve as a barometer to measure and predict society's stance and views on politics was investigated by Chauhan et al [19]. The study reviewed 38 previous works on election prediction and found that most researchers preferred the use of sentiment analysis for election prediction. It also identified challenges associated with sentiment analysis for election predictions including the activities of bot accounts, changing moods and opinions of voters, tweets with names of more than one entity making the sentiment analysis trickier, and the unavailability of a training dataset. Another work by Khan et al [23] undertook to systematically map election predictions on Twitter and comprehensively reviewed the tools, techniques and approaches utilized for election prediction on Twitter with 98 studies between 2010 and 2021. The findings showed that although elections result of 28 countries were analyzed and predicted, the elections of the United States of America (USA) and that of India formed the bulk of the election prediction analysis constituting more than 50% of the predictions. In the same vein, Mutsvairo and Ronning [21] explored the role of social media in shaping the leadership and power structures in African countries like Cameroon, Equatorial Guinea, Gambia, Ethiopia, Zimbabwe, Gabon, Ghana, Nigeria, among others. The study findings indicate while social media can be a great tool for advocating for and advancing social change and democracy, it can also be exploited by authoritarians who wish to exert control by purposefully sponsoring a suiting narrative through paid agents via social media. It highlighted that the digital divide present in many African countries has also limited the impact of the social media driven social change, referencing South Africa which has only 54% penetration rate as stated by a 2019 study. The study demonstrated that social media has strengthened civil societies in Africa, however, it concluded that while social media has increased the potentials for political activism, it has likewise opened up vistas of opportunities for manipulation, control and surveillance by authoritarian states and economic empires.

Further investigation by Mateos & Bajo-Erro [20] explored the question ‘does the digital environment galvanize and enable significantly political activism and socio-political change in Sub-Saharan Africa? The study demonstrated that online activism has amplified the onground network of activism and protests significantly to push for socio-political changes in three sub-saharan Africa nations namely Senegal, Burkina Faso and the Democratic Republic of Congo. The study pointed out that social media allows online activist to communicate easily, raise awareness and spread their messages among the online audience which increases political awareness and participation and helps to galvanize cohesion and collaboration in the push for changes. It concluded that the digital environment has been instrumental in driving social change through protests.

This review of related literature in opinion mining on matters of national interests is evident in the fact that although few works exist on sentiment analysis of hashtag digital activism, there is no lexicon-based framework that borders on extracting real live emotions of the protesters. Also, there are no works to the best of our knowledge that focuses on analyzing the #EndSARS protest and indeed all other prominent Nigeria hashtags. It is these gaps that this work seeks to fill through examining the #EndSARS and its related hashtags.

2. Materials and Methods

Works like Medhat et. al [7] and Ziani et. al [18] had shown that the Machine Learning approach can be used in sentiment extraction from texts, however, we adopted the lexicon-based approach from Liu and Hu [5] and Mohammad and Turney [8]. This is because Jurek et. al [4] showed that the standard lexicon-based sentiment analysis algorithm approach is more suitable for short messages such as tweets; and when applied with long documents, the approach would be significantly more accurate on the sentence than on the document level. This is basically the limitation of the existing Machine Learning approach. The adopted lexicon based approaches used for finding the sentiment polarity in this work are the Opinion Lexicon [5] (a list of 6800 English positive and negative opinion words) and the NRC Emotion Lexicon [8] (a list of English words and their associations with eight basic emotions - anger, fear, anticipation, trust, surprise, sadness, joy, and disgust; and two sentiments – negative and positive). The dataset used is a collection of tweets with the EndSARS hashtag and other related hashtags tabulated in Table 1.

Table 1. Number of Dataset Collected

S/N	Hashtag	Number of Tweets Extracted
1	EndSARS	3, 000
2	EndPoliceBrutality	1, 000
3	EndCorruption	543
4	EndSWAT	3, 000
5	EndBadGovernance	1, 000
6	SARSMustEnd	267
7	LekkiMassaccre	3, 000
8	LekkiGenocide	547
	Total	12, 357

A total of 12,357 tweets were collected during the period of the protest in 2020 and passed on to our EndSARS Live Analytic Framework which is demonstrated in Figure 1.

The motivation for selecting the twitter dataset is not unconnected to the fact that Twitter more than other social networks enhances academic research with global, real-time and historical data from the public conversation for free through her specialized access API endpoints. A tweet is classified as negative when there are more negative words (in various ranges) than the positive words in it, and vice-versa. The words that did not get classified into the positive and negative sentiments using the Opinion lexicons are classified as neural and may further be analyzed into their various emotions using the NRC Emotion Lexicon.

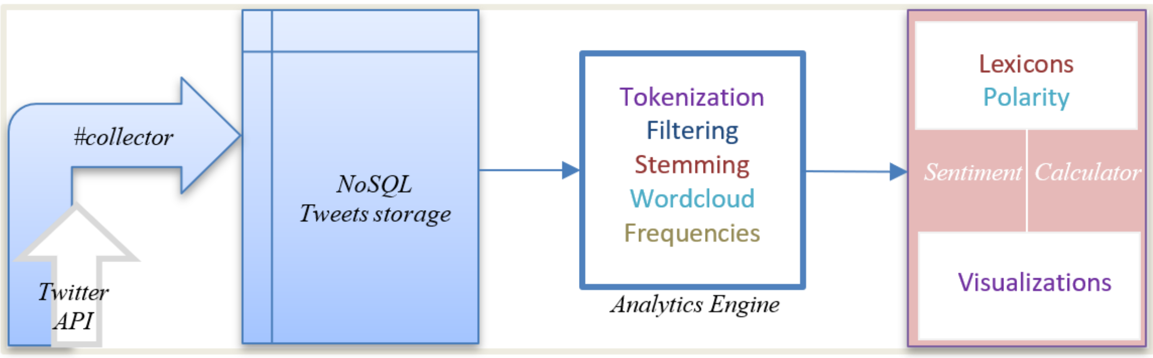

Figure 1. EndSARS live analytics framework

The tweets were collected into a NoSQL database using a hashtag collector script written in R/RStudio programming through a Twitter API. In the analytic engine, we tokenized the tweets to their words and performed some filtering tasks to remove unwanted texts like stop words, punctuations, numbers, special characters, and white spaces. Other transformations performed on the corpus includes turning the tokens to lower cases and stemming them to their root words. We also created the word cloud (Figure 2) using the Term Frequency – Inverse Document Frequency (TF-IDF) technique. Through the aid of a sentiment calculator in the script, the polarity of the tweets was finally determined using the lexicon-based approach to visually express the feelings of the protesters in eight (8) emotions as well as in positive and negative opinions.

3. Result and Discussions

The result shows the main demands of the protesters (Figure 2) and expresses the level of emotional importance to the demands (Figure 3).

Figure 2. Word Cloud of the Protest

A majority of the tweets are positively in support of the protest. In fact, Figure 3 shows that positive emotions were expressed much more than negative and people also expressed more emotions that show trust than emotions that indicate fear. This shows that the protesters and, by extension, the general public express good faith in the conduct of the movement. Many tweets were hopeful and trust that their actions will pressure the government to act positively towards the disbandment of the notorious police unit and meet the other related demands. The joy emotion was also expressed mostly as a result of the successful fundraising for the protesters towards their feeding in the protest grounds in Lagos, Nigeria. The influence of celebrities on Twitter who have large followers helped to increase the lead for the donations. There are also tweets that expressed anger, sadness, and disgust over the ills of police brutality. Others express fear towards the loss of lives and property resulting from the protest in the infamous Lekki Genocide/Massacre.

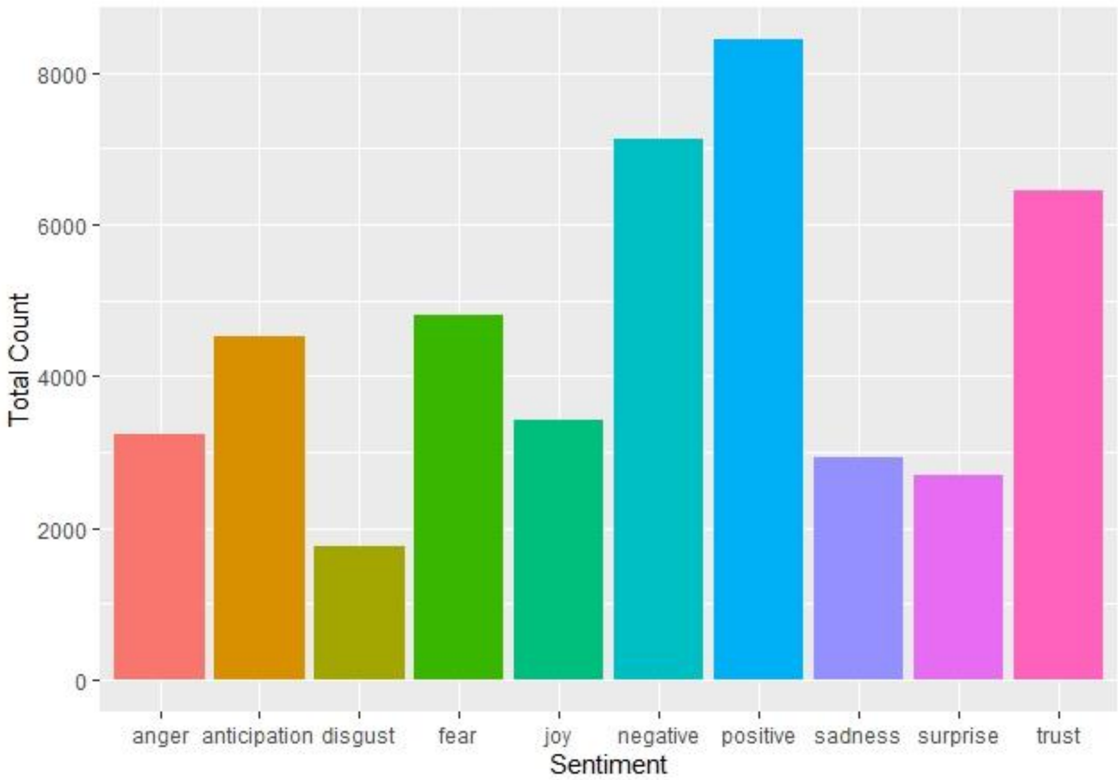

Figure 3. Emotional distribution of opinions on the EndSARS protest.

A close look at each of the demands or hashtags shows that the protesters expressed negative feelings about all the issues with some up to -4.0 negative score (Figure 4). The protest had a far-reaching effect on the other ills of the society like corruption in government and incessant industrial strike actions by the University teachers. This is demonstrated in the tweets on #endcorruption which showed the highest negative emotion (see Figure 4).

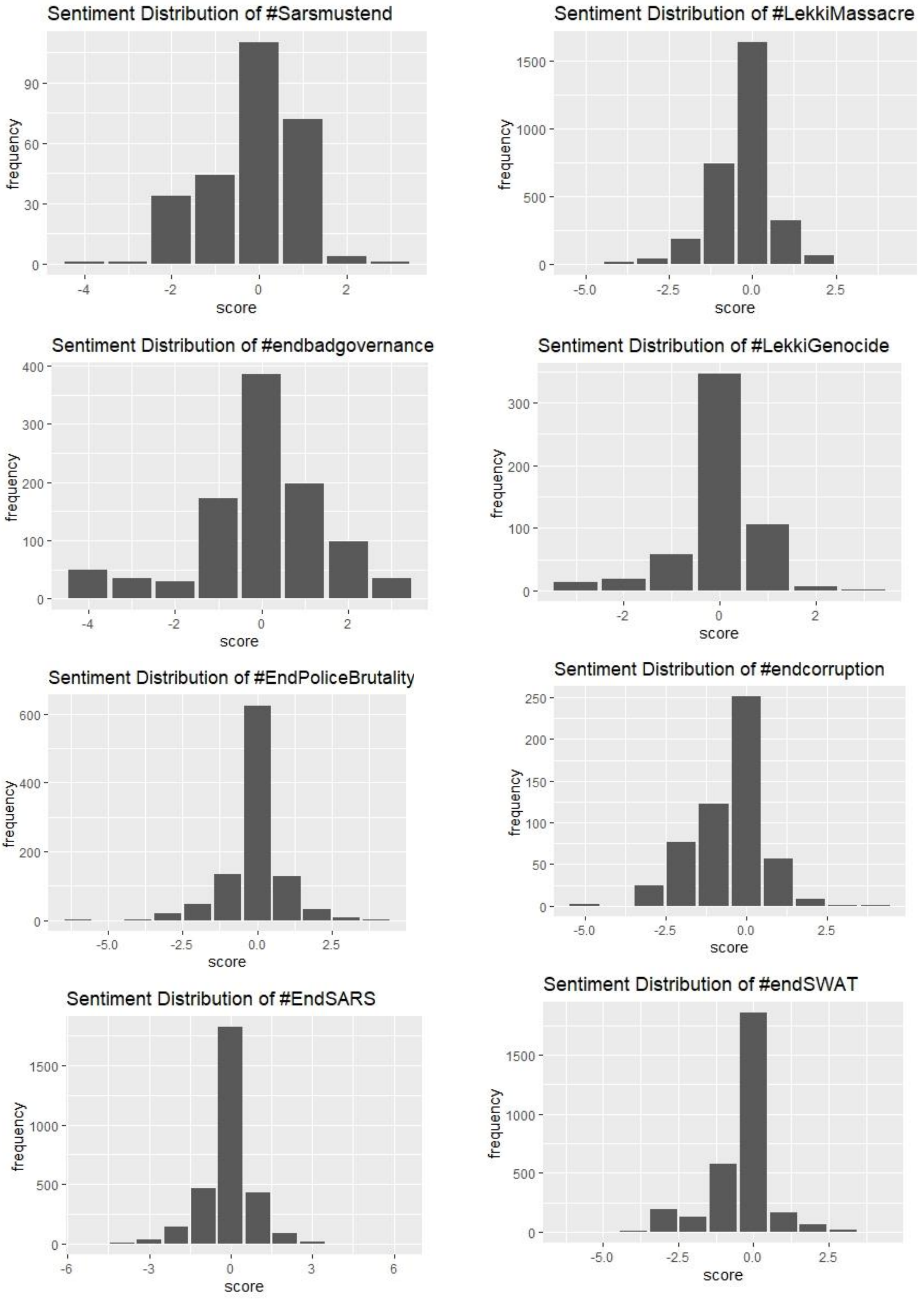

Figure 4. a: Sentiment distribution of EndSARS and its related hashtags

In Figure 5, we discovered that the trajectory of the protest was majorly negative as many tweets expressed gross emotional valence up to -6 over the period it lasted. This may not be unconnected to the periods when the government introduced SWAT in place SARS and the alleged Lekki Massacre which returned a high negative sentiment. However, there were periods when positive emotional valence was recorded which may not be unconnected to the periods when SARS was disbanded, feeding provisions made as well as when alleged hoarded palliatives were discovered.

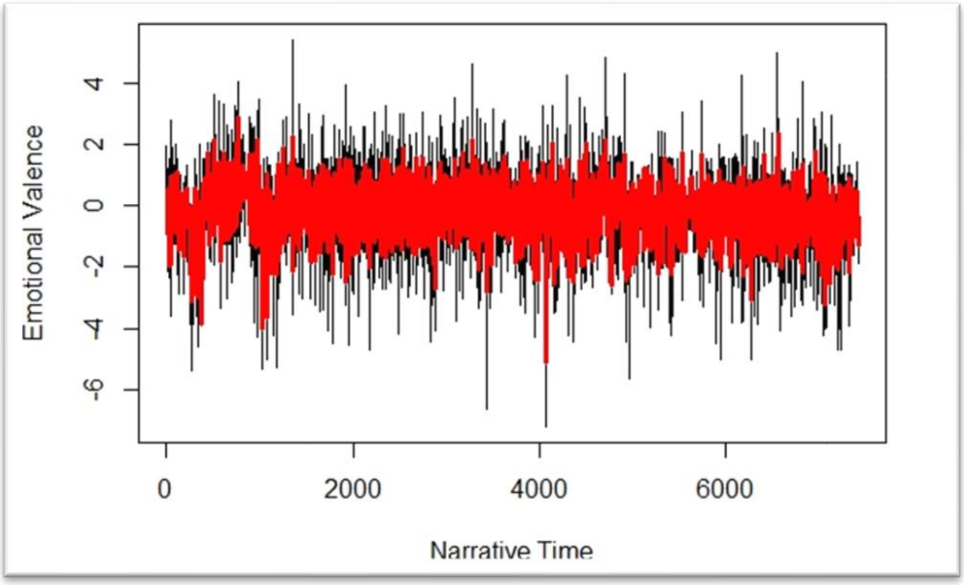

Figure 5. Plot trajectory of the protest

Although the interconnectivity of the social networks enhanced the protests, it would have largely remained online if the government had used technology as demonstrated in this work to address the concerns of the protesters. It is the failure of the government to bring timely solutions to the demands of the online protest that brought the movement to the streets across the states. The #EndSARS movement eventually became the biggest social media protest the country has seen since the #OccupyNigeria movement of January 2012. The power of the internet and the followership of celebrities and social media influencers were prominent in this. In curtailing the spread and effects of the protest, the government would have used the social media influences who led the protests online to dissuade it. Digital activism propagates with hashtags and can also be controlled with the same measure especially when opinion mining as demonstrated in this work is employed. The use of technology to extract the emotions and opinions of the protesters would have also served effective in addressing the protesters. As it is known, although the government addressed the nation later in the cause of the protest, the content of the address did not meet the actual demands of the protesters. This further led to the breakdown of law and order as the continued protests turned into the looting of public storehouses.

4. Conclusion

The work shows that digital activism can receive needed attention through a collation of the emotions expressed during the activism. Using the EndSARS protest in Nigeria, we have shown that hashtag activism gains a massive online mobilization around the topics of its protest. The result of the analysis can directly assist government in swift resolution of the matters. The application of this form of computational technology in digital movements can extract both the positive and negative emotions and the demands of the people to facilitate a more focused resolution of the issues.

References

[1] F. Brünker, M. Wischnewski, M. Mirbabaie, and J. Meinert, "The role of social media during social movements – observations from the #metoo debate on Twitter". *Proceedings of the 53rd Hawaii International Conference on System Sciences* Pg. 2356-2365, *URI: https://hdl.handle.net/10125/6403* (2020)

[2] S. Gonzalez-Bailon, J. Borge-Holthoefer, A. Rivero and Y. Moreno, "The dynamics of protest recruitment through an online network", https://arxiv.org/ftp/arxiv/papers/1111/1111.5595.pdf

[3] J. Gregorio, "The history and power of hashtags in social media marketing (Infographic)", (2014). Retrieved from https://digitalmarketingphilippines.com

[4] A., Jurek, M. D Mulvenna., and Y. Bi, "Improved lexicon-based sentiment analysis for social media analytics", *Springer Journal of Security Informatics*, *4(9)*, (2015). http://doi 10.1186/s13388-015-0024-x

[5] B. Liu, and M. Hu, "Sentiment analysis lexicons", (2005). Retrieved from https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html#lexicon

[6] M.E. Magade, "Hashtags, comment threads, and re-tweets". The emergence of young voices and alternative communicative practices for socio-political change at the time of COVID-19 in South Africa, (2020). *Global Media Journal*. https://www.globalmediajournal.com/

[7] W. Medhat, A. Hassan, and H. Korashy, "Sentiment analysis algorithms and applications", Ain *Shams Engineering Journal, 5*(4):1093-1113 (2014).

[8] S. Mohammad, and P. Turney, Lexicons", (2013). Retrieved from http://saifmohammad.com/WebPages/meetsaif.htm

[9] D. Morselli, S. Passini., and C. McGartySos, "An analysis of the anti-Maduro protest movements using Twitter", (2020). *Social Movement Studies.* doi:10.1080/14742837.2020.1770072.

[10] E. Ogbuju, A. Isa, and M. P. Abraham, "Towards a Data-driven Smart Governance in Nigeria", September. 2017. *Zenodo*. http://doi.org/10.5281/zenodo.884103

[11] E. Ogbuju, K. Taiwo, V. Ejiofor, and M. Onyesolu, "Big data-driven e-government framework in Nigeria", *Bayero Journal of Pure and Applied Sciences, 11*(2): 252 – 259, (2018).

[12] F. Oloyede and A.A Elega, "Exploring hashtag activism in Nigeria", a case of #Endsars campaign. Proceeding of 5th in Communication and Media Studies, Famagusta, Turkish Republic of Northern Cyprus. 2019. Retrieved from https://crcp.emu.edu.tr/

[13] O. Oyebode, and R. Orji, "Social media and sentiment analysis", The Nigeria presidential election of 2019. Available at: https://www.researchgate.net/publication/336812688

[14] N. Sharma, R. Pabreja, U. Yaqub, V. Atluri, S.A. Chun, and J. Vaidya, "Web-based application for sentiment analysis of live tweets, Proceedings of the 19th Annual International Conference on Digital Government Research", May 30-June 1, 2018. https://doi.org/10.1145/3209281.3209402

[15] M. Tremayne, "Anatomy of protest in the digital era, a network analysis of Twitter and occupy Wall Street, social movement studies", *Journal of Social, Cultural and Political Protest, 13(1): 110-126. DOI: 10.1080/14742837.2013.830969*.

[16] G. Yang, "Narrative agency in hashtag activism", the case of #BlackLivesMatter, *Media and Communication, 4*(4):13-17, 2016.

[17] S. Zavattro, P.E. French and D.M. Somya, "Sentiment analysis of U.S local government tweets", the connection between tone and citizen involvement. *Government Information Quarterly, 32:* 333-341. http://dx.doi.org/10.1016/j.giq.2015.03.003, 2015.

[18] A. Ziani, A. Nabiha, D. Schwab, M. Aldwairi, N. Chekkai, D. Zenakhra, and S. Cheriguene, *Recommender system through sentiment analysis.* 2nd International Conference on Automatic Control, Telecommunication, and Signals (ICATS'17), Badji Mokhtar University, Annaba, Algeria, 2017.

[19] P. Chauhan, N. Sharma, and G. Sikka. "The emergence of social media data and sentiment analysis in election prediction". Journal of Ambient Intelligence and Humanized Computing, 12(2), pp.2601-2627. 2021.

[20] O. Mateos, and C.B. Erro. "Protest, internet activism, and sociopolitical change in Sub-Saharan Africa" American Behavioral Scientist, 65(4), pp.650-665. 2021

[21] B. Mutsvairo, and H. Rønning. "The Janus face of social media and democracy? Reflections on Africa." *Media, Culture & Society* 42.3. 2020: 317-328.
[22] T. Matsilele, and P. Ruhanya. “Social media dissidence and activist resistance in Zimbabwe. Media, Culture & Society”, 43(2), pp.381-394. 2021.
[23] A. Khan, H. Zhang, N. Boudjellal, A. Ahmad, J. Shang, L. Dai, and B. Hayat. “Election Prediction on Twitter: A Systematic Mapping Study”. Complexity, 2021. 2021.