SENTIMENT ANALYSIS OF INSTAGRAM COMMENTS: A TOOL FOR EVALUATING POLITICAL POPULARITY IN POST COVID 19 ERA

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Abstract

At the fourth level of Maslow's hierarchy of needs is the esteems need. This ego-driven need compels individuals to consistently engage in self-evaluation using different parameters; one of which is comparing one's self to other members of their class. An empirical approach to this may involveengaging in popularity contest usually performed through elections or opinion polls. Rather than count ballotsspecifically casted for the purpose of such surveys, this paper took a different approach of popularity assessment supported by modern literatures to examine the sentimental bias of citizens towards political leadersthrough probing thesentiments of members of the public expressed as free comments on Instagram posts. Using the sentiment analysis feature of Natural Language Understanding (NLU) an approach supported by modern literatures, the researchers examined the sentimental bias of citizens towards President Mohammed Buhari compared to three past leaders of the country (Nnamdi Azikiwe, Obafemi Awolowo and Amino Kanu) in a bid to prove the hypothesis that 'Buhari is more popular than the formal leaders' as claimed in a statement credited to the Special Adviser to the President on Media and Publicity Femi Adesina published on October 15th, 2021 as contained in Channels Television and Punch Newspaper Instagram handles. The paper used IBM's NLU service to analyze about 2,558 comments generated by readers of the Instagram post. The study rejects the hypothesis as the result reveals that majority of the commenters shared a negative sentiment towards the person of Buhari with a value of -0.673087 and -0.865672 respectively. While that of 'Azikiwe', 'Awolowo' and 'Amino Kano' all had positives sentiments of 0.510153, 0.452324, 0.324832 respectively showing their preference.

Keywords

Sentiment Analysis, Political Popularity, Buhari, IBM Cloud, Natural Language Understanding

Introduction

Since its establishment, writing has been a major vehicle for conveying human feelings. Over the years, naturally or artificially, human opinions have been successfully mined and classifications has been made in an attempt to understand people's feeling. With the availability of different social media platforms like Twitter, Instagram, Facebook, Reddit, WhatsApp etc. and the minimal regulatory hold on them, citizens innocently take to these platforms to express their feelings about products, services, brands, people, events, and even political ideologies. As a result, a large amount of content generated by users of these platforms are available and accessible as valuable data source for identifying people's opinions about various subjects (José et al., 2016). This has been harnessed by governments, manufacturers, service providers and organization in general to gain insight of netizens' reactions concerning a discus.

At the fourth level of Maslow's hierarchy of needs is the esteems need. This ego-driven need compels individuals to consistently engage in self-evaluation using different parameters; one of which is comparing one's self to other members of their class. This can be seen in a statement credited to the special adviser to the President on Publicity, Femi Adesina on the 15th of October 2021.

> "I am old enough to have seen our colourful and even swashbuckling politicians in action. I have seen the great Obafemi Awolowo, the charismatic Nnamdi Azikiwe (Zik of Africa), Shehu Shagari, Amino Kano, M.K.O Abiola, Bashir Tofa, and many others in action. **But I have not seen anyone with the kind of attraction, magnetic pull that Muhammadu Buhari has**." And that is around the country; North and South. People swarm around him as bees do to honey," (Gbadebo, 2021; Nathaniel, 2021; Oyeleke, 2021b; Shibayan, 2021).

This attracted so much reactions from civil society, ethno-cultural organizations like Afenifere, Ohanezendi Igbo (Ikeji, 2021; Okere & Oyeleke, 2021; Oyeleke, 2021a; Silas, 2021; The Citizen Newspaper, 2021; Ugbodaga, 2021) and citizens who took to different print, electronic and social media platforms to express their views concerning the claim. Many links the poor scores of major economic indices in Nigeria between 2015 and 2021 (NBS, 2021) to leadership deficit (Obienusi & Chikwendu, 2020; Shukla, 2021) thereby vehemently disagreeing with the claims.

Although the human mind can attempt to tell if the reactions in the post showed a negative or positive sentiment, it lacks the ability to process overwhelming comments that emanated from the discourse and accurately assign a score to support its judgement. A common empirical approach to confirming the claim may be to engage in popularity contest usually performed through elections or opinion polls.

However, rather than count ballots specifically casted for surveys, this research explored the strengths of the advancement in NLU component of AI that aids the detection of the preferences of a writer in a body of text through sentiment analysis to ascertain the validity of Adesina's claim by evaluating the comments that trailed the publication of that statement on both Punch Newspaper and Channel TV's Instagram handle.

Review of Related Literature

Social media comments collected from Twitter, Facebook, Instagram, Reddit, YouTube, etc. have been used in literature as dataset in the analysis of sentiments on political views and issues.

In Matalon et al., (2021) sentiment analysis was used to predict opinion inversion on tweets of political communication. Politically-oriented discourse related to Israel with focus on the Israeli–Palestinian conflict, were explored to detect Opinion Inversion (O.I.) phenomenon. Using Random Forest model based on the Natural Language Processing features of the Source text and user attributes, they could predict whether a Source will undergo O.I. upon retweet.

Bose et al., (2019) summarized the dataset of Twitter messages related to 14th Gujarat Legislative Assembly Election, 2017, for predicting the chances of winning party by utilizing public's opinion. They used National Research Council of Canada (NRC) Emotion Lexicon to determine the overall tone of the event by eight emotions. Furthermore, deep learning tool named ParallelDots AI APIs by ParallelDots, Inc. that can analyze the sentiment into positive, negative, and neutral were used in their work. This tool helped to extract various people's sentiment and summarize the results for further decision making.

Another work which also used sentiment analysis of tweets from President Candidates of Indonesia (Jokowi and Prabowo), and tweets from relevant hashtags to predict Indonesian Presidential election result was Budiharto & Meiliana, (2018). The authors made an algorithm and method to count important data, top words and train the model to predict the polarity of the sentiment. The experimental result was produced by using R language and showed that Jokowi lead the election prediction. This prediction result corresponded to four survey institutes in Indonesia that proved that the method produced reliable prediction results.

Most literatures (Alrumaih et al., 2020; Bose et al., 2019; Elghazaly & Mahmoud, 2016) prefer twitter for such analysis since it is the most popular microblogging platform (Chi, 2020) with over 500 million tweets are posted every day (Bose et al., 2019). However, the ban on Twitter in Nigeria as at the time of this research made the researchers rule out that option.

Apart from Twitter, other social media platforms like has also been used for sentiment analysis like Facebook as in (Hand & Ching, 2020; Klimiuk et al., 2021; Sandoval-almazan & Valle-cruz, 2017; Syahriani et al., 2020), Instagram as in (Norhidayati, 2021), YouTube as in (Aufar et al., 2020). So, data from any social media platform can be used for opinion mining but the choice of which one to use is dependent on the domain of the problem, the target audience and the tools at arm.

Materials and Method

The methodological procedures used to realize the sentiment analysis were based on studies by Carvalho & Harris, (2020) whose work showed that the black-box state-of-the-arts models designed by tech gaints like IBM Cloud, Microsoft Azure, Google Coud etc. were preferable in Natural Language Processing. However, the steps taken to carryout the experiment were mostly defined in (GitHub, 2021; IBM, 2021) and implemented with author's discretion.

1. Choice of Data Source

Considering the fact that as at the time of this research, Twitter which would've been the most appropriate platform for collecting online opinions on political issues is still serving the ban imposed on it by the Federal Government of Nigeria (Nwafor, 2021; Sahara Reporters, 2021a), and the that Facebook is not favored by the print and electronic media for news sharing, Instagram was chosen.

Being that the interest was to reveal the reactions of readers on concerning Buhari's popularity claim by Adesina, we considered two media houses handles that published the news (Channels Television with 1.1million followers and Punch Newspaper with 915thousand followers) for their mass followership and active engagement.

Fig 1a: A Snapshot of Punch Newspaper Instagram Page

Source: *(PUNCH Newspapers (@punchnewspapers)* , n.d.)

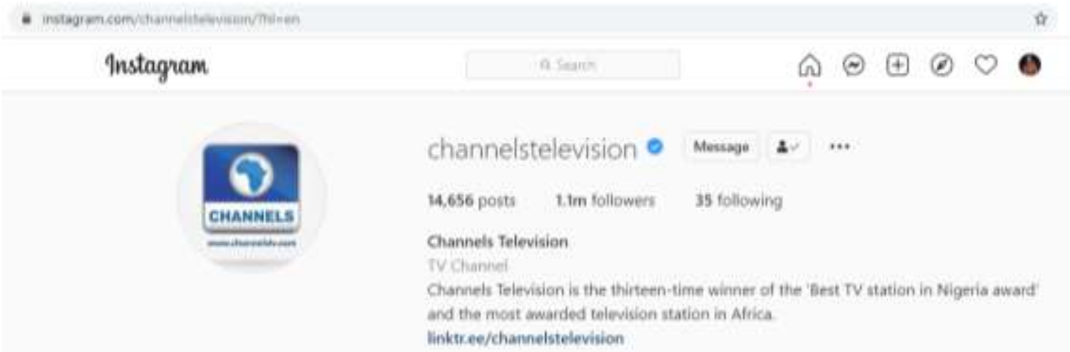


Fig 1b: A Snapshot of Channels TV Instagram Page

Source: (*Channels Television (@channelstelevision)* , n.d.)

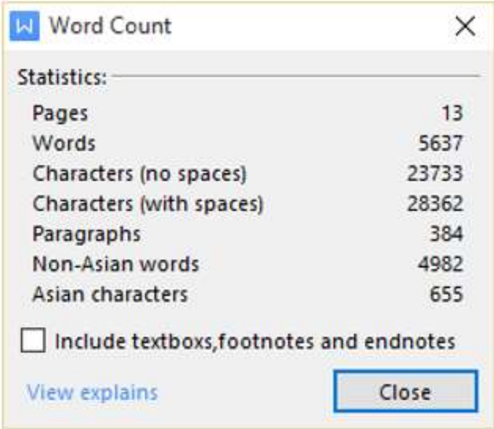
2 Corpus Collection method

The posts were opened with the urlhttps://www.instagram.com/p/CVDHzqvLqIc/ and https://www.instagram.com/p/CVDfCJtIS2L/ for Punch Newspaper and Channels Television respectively. The comments following each post were manually copied (Klimiuk et al., 2021) into separate files in WPS Office Writer and saved for pre-processing.

Punch Newspaper's post had 559 comments and 1,236 likes while Channels TV's post had 1,999 comments and 4,388 likes. This translated to a 53page Word document with commenters accounts, pictures, comment likes and reply counts for Punch while Channels TV return a 130page document.

3. Data Cleaning

In each of the files, the iconic images of account owners, comment likes and reply counts were removed to reduce their interference on the result (Klimiuk et al., 2021). This reduced the Punch dataset into a 13page document and the Channel TV dataset to 59pages as seen in Fig 2 below.



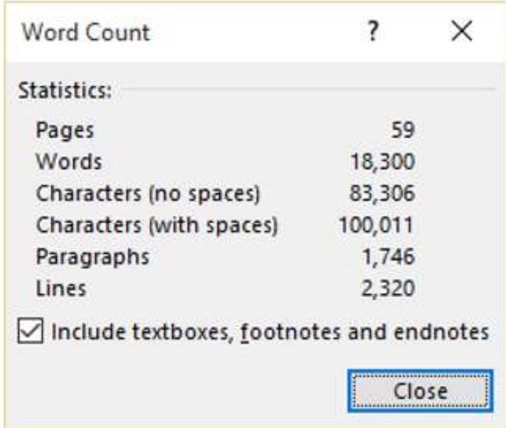


Fig 2a: Statistics of the Dataset from Punch **Fig 2b:** Statistics of the Dataset from Channels

4. Data presentation

A webpage was created on Google Sites for each dataset to make them accessible to IBM NLU service through Curl. https://sites.google.com/view/buharis-popularity-punch/home?authuser=1 for comments from Punch and https://sites.google.com/view /buharipopularity claim /home?authuser=1 for comments from Channel TV. [1]

The datasets were analyzed and reported separately because of the 50,000-character limits of the lite account of IBM Cloud which would be exceeded if the both were combined.

5. Data processing

After provisioning the NLU service on IBM cloud, the Curl command below was run on command prompt.

.

```
C:\Users\eGoodluck> curl -X POST -u "apikey:udk…S7c3DR_csmraj_x"
 --header "Content-Type: application/json" -data
 "{\"url\":\"https://sites.google.com/view/buharis-popularity-
punch/home?authuser=1\",\"features\":{\"sentiment\":{\"targets\"
:[\"buhari\",\"azikiwe\",\"awolowo\",\"amino kano\"]}}}" https:
//api.eu-gb.natural-language-understanding.watson.cloud.ibm.com/
instances/442330ec-8971-413e-bc5a-f1099fe377bc/v1/analyze?
version=2019-07-12
```

This posted the dataset to IBM Cloud and retrieved the result of the analysis in JSON format.

[1] Note that the dataset has been published by Mendeley's Digital Common Data and can be viewed with link https://data.mendeley.com//datasets/2kznsn2vn3/1 and cited as (Emereonye, 2021)

The IBM Cloud was chosen because it is the state-of-the-art black box models for NLP (Siddiqui et al., 2021) with the highest level of accuracy in sentiment scoring (Carvalho & Harris, 2020).

6. Plotting the Sentiment Score Chart

The scores from the response were tabulated in Microsoft Excel as seen in Table 1, then used to build a butterfly chart showing the sentiment scores as supported by Landon (2021). This chart can be seen in fig 3 bellow.

Result and Discussion

The result of the analysis gotten from the sentiment feature response is returned in JSON

```
C:\Windows\system32\cmd.exe

C:\Users\eGoodluck>curl -X POST -u "apikey:udb5wJkWxqMAY96e1Q42Nzd5EoS7c3DRsX4_csmraj_x" --header "Content-Type: application/json" --data "{\"url\":\"https://sites.google.com/view/buharipopularityclaim/home?authuser=1.\",\"features\":{\"sentiment\":{\"targets\":[\"buhari\"]},\"keywords\":{\"emotion\":true}}}" "https://api.eu-gb.natural-language-understanding.watson.cloud.ibm.com/instances/442330ec-8971-413e-bc5a-f1099fe377bc/v1/analyze?version=2019-07-12"
{
  "usage": {
    "text_units": 5,
    "text_characters": 50000,
    "features": 2
  },
  "sentiment": {
    "targets": [
      {
        "text": "buhari",
        "score": -0.673087,
        "mixed": "1",
        "label": "negative"
      }
    ],
    "document": {
      "score": -0.575061,
      "label": "negative"
    }
```

format and displayed in command prompt as shown in the screenshots in fig 3 below:

Fig 3a: A Screenshot of the Sentiment Feature Response from IBM NLU for Channels TV Instagram Post Comments

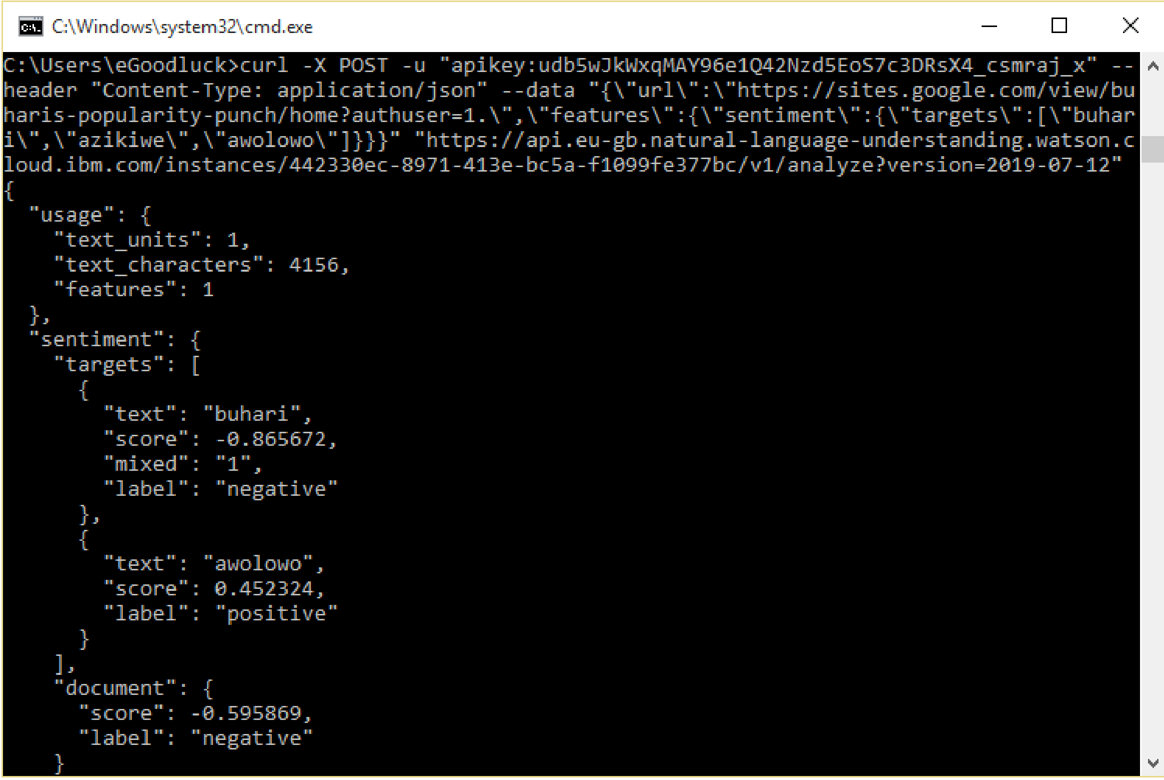


Fig 3b: A Screenshot of the Sentiment Feature Response from IBM NLU for Channels TV Instagram Post Comments

The result as seen in Table 1 shows the sentiment scores of each of the leaders derivable from the Instagram comments.The scores range from negative 1 to positive 1 while 0 indicates neutrality. The closer a score is to 1 indicates how positive the term/document is considered and the closer a score is to -1 indicates how negative the word/phrase/document is rated.

Table 1: A table showing the sentiment scores of test candidates.[2]

	Sentiment Score		
Candidate	**Punch**	**Channels**	**Average Score**
Buhari	-0.86567	-0.67309	-0.76938
Azikiwe	0.49354	0.52677	0.51015
Awolowo	0.45232	0.47229	0.46231
Amino Kano	0.37633	0.27333	0.32483
Document	-0.59587	-0.57506	-0.58547

The sentiment scores of netizens towards Buhari, Azikiwe, Awolowo and Amino Kano is shown in the chart in fig 4 below. It could be clearly seen that commenters on the post preferred the past leaders to the current one.

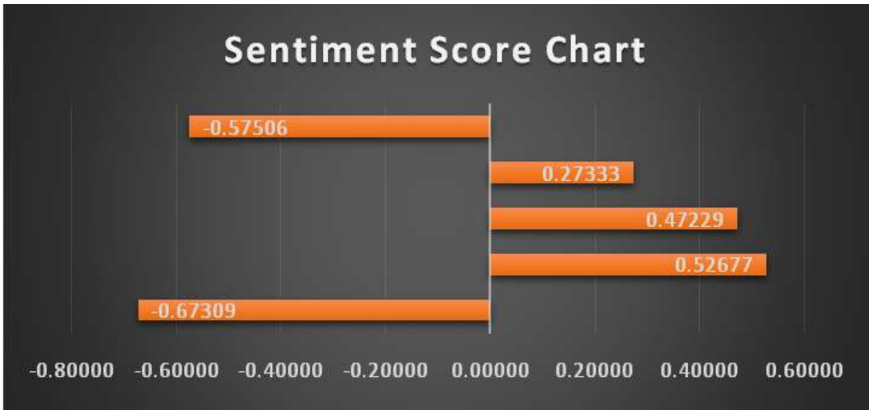


Fig 4a: A Sentiment Score Chart of the User Comments in Response to Femi Adesina's Claim

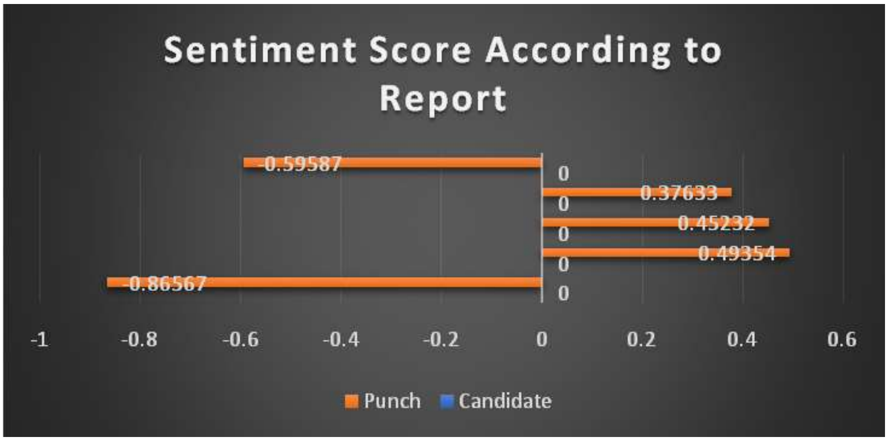


Fig 4b: Sentiment Score Chart of the User Comments According to Reports

The charts with respect to reports show that readers from Punch had more sharp disagreement with the claims than those from Channels. They also were less excited than those of Channels TV about the other past leaders except for Amino Kanu who they favored more than those of Punch Newspaper.

From the foregoing, it can be inferred that all the former leaders mentioned in the post under review had positive sentiments unlike the present President Buhari who had an average score of -0.76938.

To validate these scores, the dataset was put together and tested on Monkey Learn platform, this also returned a negative score of 75.4% for Buhari in agreement with our result. This therefore clearly agrees with the response of the publicity secretory of Afanifere that "Comparing President Buhari to Chief Obafemi Awolowo and Dr Nnamdi Azikiwe therefore is not only mistaken; it is mischievous, to say the least," (Agboluaje, 2021; Ikeji, 2021; Okere & Oyeleke, 2021; Oyeleke, 2021a; Sahara Reporters, 2021b; Ugbodaga, 2021) and that of Ohanezendi Igbo that "unfortunately, one cannot compare these personalities with Buhari. And that "as a matter of fact, even Adesina knows that what he said is not true" (Akpa, 2021; Okere & Oyeleke, 2021; Silas, 2021; The Citizen Newspaper, 2021).

Conclusion and Recommendations

Sentiment analysis can help derive a quantitative score from the qualitative expressions of the everyday citizens in the comments of social media post as it explicitly indicates/reflects the judgement of the netizens towards a political figure. The research shows that the readers of the presidential spokesperson's claim of his principal's popularity among Nigeria's former leaders vehemently disagree with the claims.

The authors therefore recommend the use of established opinion mining tools to measure the public preferences from time to time as to avoid provocative claims that further diminishes the mental health of citizens in this post covid 19 era.

Limitation

Exclusion of emoticons is a limitation in this study. Although these are important instrument for expressing opinions on social media, this research excluded them in its evaluation because we handled only textual comments.

Suggestion for Future Research

Sentiment analysis has gained the interest of researchers as seen in many recent publications (Singh et al., 2020). However, there's need for further research to help bring Natural Language Understanding (NLU) as close as possible and probably surpass the human mind by improving its ability to detect and correctly classify:

- **Sarcasm:** though a sarcastic sentence may contain what looks like a positive comment to SA, it is aimed at creating humor that is aimed at mocking with irony (Kranjc et al., 2015).
- **Local Slangs, Code-switching and Code-mixing:** Free comments usually contain a lot of slangs, code-switching and code-mixing which the state-of-the-art NLU models are still unable to handle (Birshert & Artemova, 2021).

Researches that will improve these areas will most definitely at value to the clarity of insights obtained through sentiment analysis.

References

Agboluaje, R. (2021, October 16). Comparing Buhari with Awolowo, Azikiwe mischievous —Afenifere. *The Guardian*. https://guardian.ng/news/comparing-buhari-with-awolowo-azikiwe-mischievous-afenifere/

Akpa, N. (2021, October 18). Don't compare Buhari with Azikiwe, Awolowo, Ohanaeze slams Adesina . *The Guardian Nigeria News* . https://guardian.ng/news/dont-compare-buhari-with-azikiwe-awolowo-ohanaeze-slams-adesina/

Alrumaih, A., Al-Sabbagh, A., Alsabah, R., Kharrufa, H., & Baldwin, J. (2020). Sentiment analysis of comments in social media. *International Journal of Electrical and Computer Engineering*, *10*(6), 5917–5922. https://doi.org/10.11591/ijece.v10i6.pp5917-5922

Aufar, M., Andreswari, R., & Pramesti, D. (2020). Sentiment Analysis on Youtube Social Media Using Decision Tree and Random Forest Algorithm: A Case Study. *2020 International Conference on Data Science and Its Applications, ICoDSA 2020*. https://doi.org/10.1109/ICoDSA50139.2020.9213078

Birshert, A., & Artemova, E. (2021). Call Larisa Ivanovna : Code-Switching Fools Multilingual NLU Models. *Aist*, *i*.

Bose, R., Dey, R. K., Roy, S., & Sarddar, D. (2019). *Analyzing Political Sentiment Using Twitter Data*. Springer Nature Singapore Pte Ltd. https://doi.org/10.1007/978-981-13-1747-7

Budiharto, W., & Meiliana, M. (2018). Prediction and analysis of Indonesia Presidential election from Twitter using sentiment analysis. *Journal of Big Data*, 1–10. https://doi.org/10.1186/s40537-018-0164-1

Carvalho, A., & Harris, L. (2020). Off-the-Shelf technologies for sentiment analysis of social media data: Two empirical studies. *26th Americas Conference on Information Systems, AMCIS 2020*, 1–10.

Channels Television (@channelstelevision) . (n.d.). Instagram. Retrieved November 8, 2021, from https://www.instagram.com/channelstelevision/

Chi, C. (2020, November 19). *The Short & Sweet Guide to Microblogging*. https://blog.hubspot.com/marketing/micro-blogging

Elghazaly, T., & Mahmoud, A. (2016). *Political Sentiment Analysis Using Twitter Data*.

Emereonye, G. (2021). *Instagram Comments on Channels TV News Handle over President Buhari's Popularity Claim by Femi Adesino* (Vol. 1). Mendeley Data. https://doi.org/10.17632/2KZNSN2VN3.1

Gbadebo, B. (2021, October 15). President Buhari More Popular Than Azikiwe, Awolowo, Shagari – Adesina. *Leadership Newspaper*. https://leadership.ng/president-buhari-more-popular-than-azikiwe-awolowo-shagari-adesina/

GitHub. (2021, September 30). *Getting started with Natural Language Understanding*. IBM Cloud Docs. https://cloud.ibm.com/docs/natural-language-understanding?topic=natural-language-understanding-getting-started#getting-started-tutorial

Hand, L. C., & Ching, B. D. (2020). Maintaining neutrality: A sentiment analysis of police agency Facebook pages before and after a fatal officer-involved shooting of a citizen. *Government Information Quarterly*, *37*(1), 101420. https://doi.org/10.1016/j.giq.2019.101420

IBM. (2021, September 9). *Natural Language Understanding*. IBM Cloud API Docs. https://cloud.ibm.com/apidocs/natural-language-understanding

Ikeji, L. (2021, October 15). Afenifere tackles Adenisa for comparing Buhari to Awolowo and Azikiwe. *Linda Ikeji Blog*. https://www.lindaikejisblog.com/2021/10/afenifere-tackles-adenisa-for-comparing-buhari-to-awolowo-and-azikiwe.html

José, D., Oliveira, S., Henrique, P., Bermejo, D. S., José, D., & Oliveira, S. (2016). *Can social media reveal the preferences of voters ? A comparison between sentiment analysis and traditional opinion polls sentiment analysis and traditional opinion polls*. *1681*(August). https://doi.org/10.1080/19331681.2016.1214094

Klimiuk, K., Czoska, A., Biernacka, K., & Balwicki, Ł. (2021). Vaccine misinformation on social media–topic-based content and sentiment analysis of Polish vaccine-deniers' comments on Facebook. *Human Vaccines and Immunotherapeutics*, *17*(7), 2026–2035. https://doi.org/10.1080/21645515.2020.1850072

Kranjc, J., Smailović, J., Podpečan, V., Grčar, M., Žnidaršič, M., & Lavrač, N. (2015). Active learning for sentiment analysis on data streams: Methodology and workflow implementation in the ClowdFlows platform. *Information Processing and Management*, *51*(2), 187–203. https://doi.org/10.1016/J.IPM.2014.04.001

Matalon, Y., Magdaci, O., Almozlino, A., & Yamin, D. (2021). Using sentiment analysis to predict opinion inversion in Tweets of political communication. *Scientific Reports*, 1–9. https://doi.org/10.1038/s41598-021-86510-w

Nathaniel, S. (2021, October 15). Buhari More Popular Than Azikiwe, Awolowo, Aminu Kano – Adesina. *Channels Television*. https://www.channelstv.com/2021/10/15/buhari-more-popular-than-azikiwe-awolowo-aminu-kano-adesina/

NBS. (2021). *Nigeria's Current Statistical Indicies*. https://www.nigerianstat.gov.ng/

Norhidayati, M. (2021). *Impression Flow Based on Comment in Islamic Studies from Instagram Using Sentiment Analysis*. *20*(1), 42–56.

Nwafor, S. (2021, October 1). Breaking: Buhari lists conditions for lifting of Twitter ban. *Vanguard Media Limited, Nigeria*. https://www.vanguardngr.com/2021/10/breaking-buhari-lists-conditions-for-lifting-of-twitter-ban/

Obienusi, I. E., & Chikwendu, C. P. (2020). Political Leadership and Nigeria's Economy Since 1999. *Kenneth Dike Journal of African Studies*, *1*(2), 152–177. https://www.nigerianjournalsonline.com/index.php/KDJAS/article/view/1393

Okere, A., & Oyeleke, S. (2021, October 16). Afenifere, Ohanaeze slam Adesina, say comparing Buhari to Awolowo, Azikiwe mischievous - Punch Newspapers. *Punch Newspaper*. https://punchng.com/afenifere-ohanaeze-slam-adesina-say-comparing-buhari-to-awolowo-azikiwe-mischievous/

Oyeleke, S. (2021a, October 15). *Comparing Buhari to Awolowo, Azikiwe mischievous, Afenifere slams Adesina*. https://punchng.com/comparing-buhari-to-awolowo-azikiwe-mischievous-afenifere-slams-adesina/

Oyeleke, S. (2021b, October 15). Why Nigerians are more attracted to Buhari than Awolowo, Nnamdi Azikiwe -Adesina. *Punch Newspaper*. https://punchng.com/why-nigerians-are-more-attracted-to-buhari-than-awolowo-nnamdi-azikiwe-adesina/

PUNCH Newspapers (@punchnewspapers) . (n.d.). Instagram. Retrieved November 8, 2021, from https://www.instagram.com/punchnewspapers/?hl=en

Sahara Reporters. (2021a, October 1). Twitter Reacts To Buhari's Conditional Lifting Of 4-Month Ban. *SAHARAREPORTERS, NEW YORK*. http://saharareporters.com/2021/10/01/twitter-reacts-buhari's-conditional-lifting-4-month-ban

Sahara Reporters. (2021b, October 16). Comparing Buhari To Awolowo, Azikiwe Mischievous – Afenifere Slams Femi Adesina | Sahara Reporters. *Sahara Reporters*. http://saharareporters.com/2021/10/16/comparing-buhari-awolowo-azikiwe-mischievous-–-afenifere-slams-femi-adesina

Sandoval-almazan, R., & Valle-cruz, D. (2017). *Facebook Impact and Sentiment Analysis on Political Campaigns*.

Shibayan, D. (2021, October 15). Femi Adesina: Nigerians are more attracted to Buhari than Azikiwe, Awolowo. *The Cable*. https://www.thecable.ng/femi-adesina-nigerians-are-more-attracted-to-buhari-than-azikiwe-awolowo

Shukla, S. (2021). An Analysis of Economic Philosophy and Leadership in Ancient India. *Journal of Applied Business and Economics*, *23*(5), 159–164. https://doi.org/10.33423/jabe.v23i5.4570

Siddiqui, S., Rasool, G., & Ramachandran, R. P. (2021). The Case against Sentiment Analysis for Natural Text. *Proceedings of the International Joint Conference on Neural Networks*, *2021-July*. https://doi.org/10.1109/IJCNN52387.2021.9533870

Silas, D. (2021, October 16). Azikiwe, Awolowo, others are incomparable to Buhari in all standards - Ohanaeze replies Femi Adesina - Daily Post Nigeria. *Daily Post Media Ltd*. https://dailypost.ng/2021/10/16/azikiwe-awolowo-others-are-incomparable-to-buhari-in-all-standards-ohanaeze-replies-femi-adesina/

Singh, N. K., Tomar, D. S., & Sangaiah, A. K. (2020). Sentiment analysis: a review and comparative analysis over social media. *Journal of Ambient Intelligence and Humanized Computing*, *11*(1), 97–117. https://doi.org/10.1007/s12652-018-0862-8

Syahriani, Yana, A. A., & Santoso, T. (2020). Sentiment analysis of facebook comments on indonesian presidential candidates using the naïve bayes method. *Journal of Physics: Conference Series*, *1641*(1). https://doi.org/10.1088/1742-6596/1641/1/012012

The Citizen Newspaper. (2021, October 18). *Don't compare Buhari with Azikiwe, Awolowo - Ohanaeze warns Adesina*. https://thecitizenng.com/dont-compare-buhari-with-azikiwe-awolowo-ohanaeze-warns-adesina/

Ugbodaga, K. (2021, October 15). Comparing Buhari to Awolowo, Azikiwe mischievous: Afenifere blasts Adesina - P.M. News. *PM News*. https://pmnewsnigeria.com/2021/10/15/comparing-buhari-to-awolowo-azikiwe-mischievous-afenifere-blasts-adesina/

Umaru, A. (2021). *Overview of Mid-Term Scorecard and Summary of Ministerial and MDA Performance*. Nigeria Governor's Forum. http://ngfrepository.org.ng:8080/jspui/handle/123456789/4848