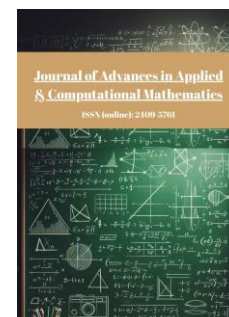




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A Computational Sentiment Analysis of Public Opinion on Nigerian 2023 Presidential Candidates from YouTube Video Comments

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ABSTRACT

YouTube has become an important platform for public expression, where users post comments to communicate their views and feelings about political issues and candidates. This study examined public sentiment and prominent words associated with presidential aspirants in Nigeria's 2023 presidential election using YouTube comments. Comments available online for 16 presidential aspirants who declared their intention to contest the 2023 presidential election were collected using the Google YouTube Data API. Sentiment analysis and word-cloud analysis were performed to identify the dominant emotional patterns and frequently occurring terms in the comments. In addition, the sentiment classifier was evaluated against a gold-standard annotated dataset using accuracy, precision, recall (sensitivity), F1-score, specificity, negative predictive value, balanced accuracy, and Cohen's kappa to assess its classification performance and agreement beyond chance. The results showed that negative sentiment constituted the largest proportion of the comments, followed by positive sentiment, whereas surprise had the lowest proportion. The most frequently occurring word was "Nigeria," while the names "Tinubu," "Sowore," and "Orji Kalu" were prominent in the word cloud. The classifier achieved an accuracy of 78.39%, with a positive-class precision of 62.94%, recall of 93.04%, F1-score of 75.09%, specificity of 70.49%, negative predictive value of 94.95%, balanced accuracy of 81.77%, and Cohen's kappa of 0.5722. These findings demonstrate the sentiment patterns expressed in YouTube comments surrounding the 2023 Nigerian presidential election and provide an empirical assessment of the reliability of the sentiment classification approach.

1. Introduction

The 2023 Nigerian presidential election generated extensive online discourse across social media platforms, particularly YouTube, where political campaign videos, debates, and news commentary attracted large volumes of user-generated comments. These comments provide rich, real-time public opinion data that can be mined using Natural Language Processing (NLP) and sentiment analysis techniques [1-3]. Sentiment analysis (SA) is a rapidly growing field that creates methods for extracting insight from polarised content [1, 4-11]. SA is also called emotion artificial intelligence. It is the study of opinions and can be used in prediction [12-14]. The SA of users aids in determining the percentage of users who favour, oppose, or are neutral on the topic [2, 14-16]. Social media is an important communication tool that has grown at an exponential rate in recent years. It is relevant in a variety of circumstances because it lets users express themselves, share content, and spread news [16, 17]. Online social networks such as Twitter and Facebook are virtual venues where people may connect with others who share their interests by exchanging various sorts of media materials such as posts, links, and photos [18]. SA has been applied to know the feedback of the public from YouTube videos and used the cross-domain concept to construct a model of positive or negative opinion labelling in Indonesian society [19]. SA has been solved using machine learning algorithms [12, 20, 21].

The internet of things has made communications easier and created easy access to social media sites and platforms. The top sites and platforms are WhatsApp, Facebook, Instagram YouTube, TikTok, Reddit, SnapChat, Twitter, Linkeldn, and Pinterest. We can use paper-based or face-to face- interview to collect and collate comments from the public on a particular issue, but to have access to wider audience, we decided to make use of online YouTube social media comments, because a lot of people post their comments on this particular social media. Google owns YouTube, an American real-time video sharing and social media platform. YouTube was established on February 14, 2005, and as of 2021, it had revenue of \$28.8 billion.

A lot of researchers have worked on SA but not on using YouTube comments, especially on politics. The methodology in this study can be applied to any similar case to obtain an SA. The purpose of this study is to find sentiments, draw a word cloud, and compute the average age of the presidential aspirants in the 2023 election in Nigeria. Another name for word cloud is word collage; it represents virtual representations of words that appear most. This study is crucial because we did not find in the literature where SA was used on comments on political comments on YouTube videos. The studies we found in the literature on the SA of YouTube comments did not apply to political comments.

We generated the word cloud for the comments extracted from online YouTube videos when the aspirants declared their intentions to vie for the office of Nigeria's number one citizen in preparation for the elections coming up in February 2023. Nigeria currently has a population of 216.7 million, based on projections. We did not find any article in the literature where SA was used on YouTube videos in Nigeria.

To achieve the purpose of the research, we extracted data from YouTube videos with the help of an API Google Developer key and analysed it. But before we can analyse the comments that we have extracted, we need to clean the data because most of the comments will be unclean. By "unclean data," we mean the data will contain duplicate words, wrong data, missing attributes, noise, and improperly formatted data. There is a need to remove anything in the comments that could lead to incorrect results or information.

The contribution of this study lies in its integration of large-scale YouTube comment analysis, sentiment and word-frequency analysis, and independent gold-standard validation to examine online public opinion surrounding all 16 presidential aspirants in Nigeria's 2023 presidential election. Beyond identifying dominant sentiment patterns, the study quantitatively evaluates the reliability of the sentiment classifier using multiple diagnostic measures, thereby providing a methodological contribution to computational political discourse analysis in the Nigerian context.

2. Related Work

Fagbola & Thakur [22] applied lexicon-based public opinion and predicted the winner of the election conducted in Nigeria in 2019, using SA. The authors used 225,500 tweets related to the two major political parties in Nigeria. The sentiments were divided into positive and negative categories using Plutchik's wheel of emotion. The results of this study correctly predicted the winner of the 2019 election in Nigeria. We have learned in this paper that SA can be used on Twitter data to forecast the winner of an election.

Onyenwe *et al.* [23] concentrated on the SA of the impact of a political party using Twitter tweets to decide the candidate who wins an election. Five major candidates and their parties: Willie Obiano is the candidate of the All Progressive Grand Alliance (APGA), Tony Nwoye is from the All Progressives Congress (APC), Oseloka Obaze is from the People's Democratic Party (PDP), Osita Chidoka is from the United Progressive Party (UPP), and Godwin Ezeemo is from the People's Progressive Alliance (PPA). For this purpose, a set of 7,430 tweets bearing on or related to #AnambraDecides2017 were streamed during the Anambra State gubernatorial election on November 18, 2017. These are Twitter conversations about the top five political parties and their candidates, who are referred to as "political actors" in this paper. The authors conducted polarity and subjectivity sentiment analyses on all tweets, taking time into account as a useful dimension of SA. The topics that were highly discussed were discovered with the help of a modelling algorithm and how to compute the sentiments with the most frequent words that have relationships with the topics for each political actor. From this study, we learned that SA can be used to determine the acceptability of a candidate or party using Twitter data.

Alhujaili & Yafooz [24] reviewed articles on the SA of YouTube videos with the user's comments, the methodology and techniques employed to study the SA. The SA was divided into three categories: simple, complex, and advanced. For a simple SA, the comments were grouped into three categories: negative, neutral, and positive. In complex SA, we have at least five classes like sad, fearful, happy, surprised, angry, etc. Simple and complex SA use machine language techniques, but complex SA involves a Lexicon-based method. This study has provided a deep understanding of the work on SA using YouTube video comments.

Singh & Tiwari [25] conducted research to assist researchers in classifying good research articles using SA. The authors collected data from comments on YouTube and the attitude of the users' comments. SA was used on the large amount of text data to fathom the opinions of the users. To achieve the purpose, machine learning classifiers such as random forest, support vector machine, Naïve-Bayes, logistic regression, decision tree, and k-nearest neighbour were used in conjunction with other measures for result optimization. The authors used evaluation metrics such as F-score and accuracy score. We learned in this study that support vector machine performed better when compared to the other approaches.

Chinedum & Ogochukwu [26] devices a designed and enhanced structure designed for the social media contents that used modified Lesk algorithm on social media data pre-processing. The study revealed that the method applied was better than the existing approaches for opinion mining from Nigerian-Igbo tweets when it was applied to supervised learning algorithms.

De Guzman *et al.* [27] aim is to understand the ontology and expressive valences evident among virtual viewers of senior adults' auditions for Got Talent shows using YouTube video opinions. Senior adults' audition videos for Got Talent that contain non-English comments were excluded from the study. Quantitative SA was done on social media comments mined from YouTube videos through data mining. The paper used cross-case and within-comment analyses of comments posted. We learnt in the research about emotional valence using older people talents showcased in a competition that is international. In addition, we learnt that the online viewers emotions of the senior adults revealed four emotional spaces of inspirational, appreciative, emulative, and depreciative.

Tehreem & Hira [28] focused on the comments in Roman Urdu on YouTube comments based on many Pakistan TV and drama shows. On Facebook, Twitter, and YouTube, there is a wealth of information in the Roman-Urdu language. Five different supervised learning algorithms, which are support vector machine, linear regression, multi-layer perception, the Naive-Bayes classifier, and the K-Nearest Neighbor algorithm, were compared. Support vector

machine performed better, with an accuracy of 64%. This study has shown that the right supervised machine learning method can be used to understand the sentiments of Roman Urdu language comments on YouTube.

Muhammad *et al.* [29] studied Twitter comments available online in four major languages in Nigeria. The languages are Igbo, Yoruba, Hausa, and Nigerian-Pidgin. The dataset comprises 30,000 annotated tweets in each language and 14,000 in Nigerian-Pidgin. To get datasets for the languages, the authors suggested processing, text collection, labelling, and filtering. With the help of transfer methods and pre-trained models on the data, models that are language-specific with language-adaptive fine-tuning mostly worked best. This paper has shown that SA can be used for Nigerian indigenous languages.

Fowobaje *et al.* [30] used SA to perform a qualitative content analysis of the ascension and inaugural addresses of Nigerian heads of state and presidents from 1960 to 2019. The summary of the words and characters in the ascension and inaugural addresses showed that the civilian presidents used more characters and words than the military heads of state. The sum of the sentiment score in the ascension/inauguration speeches from 1960 to 2019 by civilian presidents and military heads of State showed that the civilian presidents voiced more surprise, trust, sadness, fear, joy, disgust and anticipation in their speeches than the Military Heads of State. We have learned in this paper that SA can be used to know the emotions of speeches by politicians.

AminiMotlagh *et al.* [31] used data mining classifiers, such as decision tree, K-nearest neighbour, naive Bayes and support vector machine, to analyse tweet sentiment. Support vector machine performed better when compared to the other algorithms. Two datasets were used with two classes (negative and positive) and then a three-class dataset (negative, positive, and neutral). Two ensemble approaches were used to decrease the bias and variance of the learning algorithms. We have learned in this paper that SA can be used to analyse tweets.

The preceding discussion highlighted developments in sentiment analysis and political discourse studies related to Nigeria's 2023 presidential election, drawing on both foundational studies published before 2023 and more recent contributions. To provide a concise comparison of the major studies, their methodologies, key findings, and research gaps, Table 1 summarizes relevant studies published between 2023 and 2025.

Table 1: Summary of Recent Studies on Sentiment Analysis and Political Discourse Related to Nigeria’s 2023 Presidential Election (2023–2025)

Study/Data Source	Methodology	Key Findings	Relevance to the Present Study
[32] Twitter dataset (Tinubu, Atiku, Obi)	LSTM, PLSTM, TSR-LSTM deep learning models	TSR-LSTM achieved superior accuracy in classifying positive, neutral, and negative sentiments	Provides foundational ML framework applicable to YouTube comment sentiment classification
[33] 2 million tweets	NLP, LSTM, BERT, LSVC models	Strong polarization across candidates; BERT and LSVC improved classification robustness	Demonstrates scalable NLP pipeline adaptable to YouTube political discourse
[34] YouTube captions (street interviews)	ChatGPT-based annotation, opinion mining framework	ChatGPT effectively predicts voting intention with high accuracy	Shows feasibility of YouTube-based electoral sentiment extraction using AI models
[35] YouTube video comments/descriptions (2023–2024)	VADER, Detoxify, LDA topic modeling	Mixed sentiment distribution; YouTube supports large-scale opinion mining and toxicity detection	Demonstrates YouTube's suitability for sentiment + toxicity analysis frameworks
[36] Social media memes (Facebook/WhatsApp)	Qualitative CDA + multimodal analysis	Political content expressed protest against governance and economic hardship	Supports interpretation of negative sentiment narratives in Nigerian political discourse
[37] INEC electoral + socioeconomic datasets	Multinomial logit + spatio-temporal modeling	Voting behavior strongly linked to HDI and regional socioeconomic variation	Provides explanatory context for sentiment differences observed in YouTube comments

3. Materials and Methods

3.1. Extraction of Data

The source of the data was comments on YouTube videos. Comments can be extracted from YouTube videos with the aid of a Google developer API key [38, 39]. To achieve this purpose, we used a library function in the R programming language called 'vosonSML' [40], which replaced 'SocialMediaLab'. The 'SocialMediaLab' has been removed from the CRAN repository.

This new package, "vosonSML" was built under R version 4.1.3. The package can be used to mine data from social networking sites, and it is very easy to use. We proceeded by using the API key, the key can be obtained from the Google cloud console [41]. The 'authenticate' object was used as a credential object for R to authenticate the link to the social network API. The comments were retrieved on 18th March, 2022 and covered the candidates who declared to vie for the post of president in Nigeria before that date. To retrieve the data, we use the YouTube video IDs. In this research, 18 YouTube videos IDs on 16 presidential aspirants in 2023 election in Nigeria (See Table 2). For each comment, we have 12 variables, like comments, author display name, authorprofileImageUrl, presentID, videoID, etc. Since we only need the comments variable for the sentiment's analysis, we focus on the comments online on those YouTube videos of only presidential aspirants who declared their intentions to vie for the post of number one citizen in Nigeria, a country with over 216.7 million population based on projections and has 36 states and a capital city called Abuja. Fig. (1) depicts the materials and methods process, while Fig. (2) depicts the data extraction process.

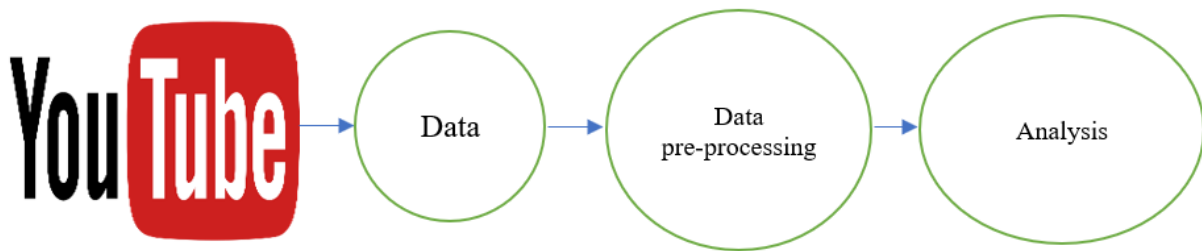


Figure 1: Schematic representation of the work.



Figure 2: Extraction of data procedure.

Sentiment analysis of the YouTube comments was conducted in R using the NRC Emotion Lexicon, implemented through the `get_nrc_sentiment()` function in the `syuzhet` package (version 1.0.7). The NRC lexicon provides word-level associations with positive and negative sentiment and eight basic emotions: anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. For classifier validation, a subset of 657 comments was independently annotated by two human annotators. The comments were selected as a validation subset for independent human annotation. The subset was selected using random sampling to reduce selection bias and provide an independent representation of the full comment corpus. Two human annotators independently classified the selected comments, and their annotations were treated as the gold-standard labels for evaluating the automated sentiment classifier. The annotators assigned each comment to one of two sentiment categories, Positive or Negative, without access to the classifier's predictions. The two sets of annotations were compared using Cohen's kappa (κ) to assess inter-annotator agreement. Disagreements were subsequently resolved through adjudication to establish the gold-

standard sentiment labels. The classifier predictions were then compared with these gold-standard labels, and the resulting confusion matrix is presented in Table 3.

3.2. Pre-processing of Data

The natural language processing (NLP) deals with text data, but before we can analyse the comments that we have extracted, we need to clean the data [42], because most of the comments will be unclean. By "unclean data," we mean the data will contain duplicate words, wrong data, missing attributes, noise, and improperly formatted data. There is need to remove anything in the comments that can mislead these results or give wrong information. The cleaned datasets are better for analysis. Before doing the analysis, we can use sampling, aggregation, dimensionality reduction, and discretization [43, 44]. To clean the YouTube comments we collected with the help of an API key from Google Developer. To achieve this purpose, we used 'tm_map' function in R to remove stopwords, convert the comments to lower case, and remove the unwanted white spaces. As part of the procedure of cleaning the data, we changed all the comments to lower case, removed all the punctuation in the comments, and all the numbers. In addition, we equally remove some words that will not be adding any value to the comment. Fig. (3) represents the data cleaning procedure and Fig. (4) shows the process of the analysis.

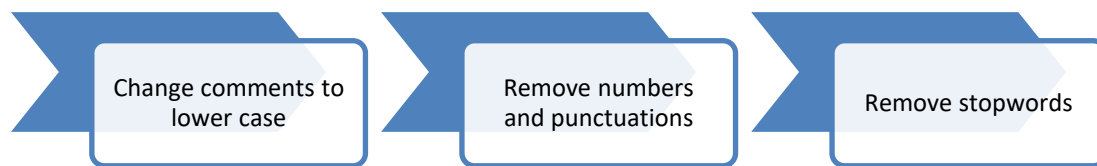


Figure 3: Procedures for data cleaning.

3.3. Implementation of SA and Analysis

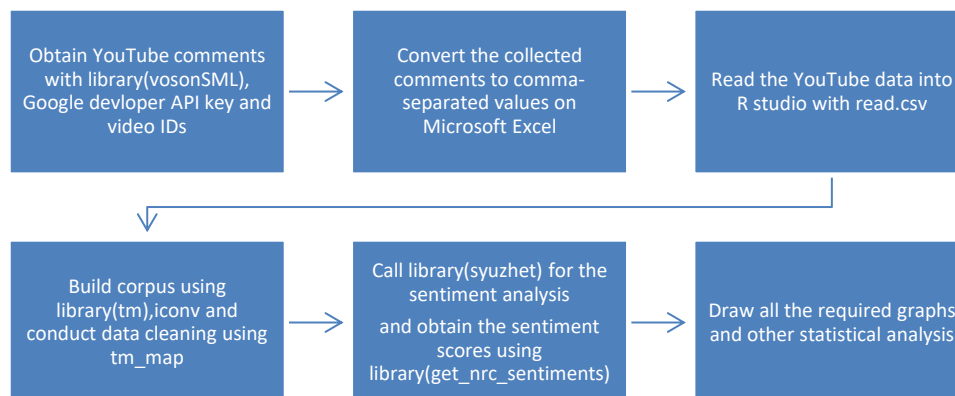


Figure 4: Process of the analysis.

4. Results and Discussion

In this research, to achieve the purpose we stated in the introduction section, we obtained a total of 5,083 comments, where all YouTube comments were in English, with no Nigerian Pidgin, Yoruba, Igbo, or Hausa comments identified. Thus, the dataset had a homogeneous language composition (100% English). Consequently, the reported classification performance reflects English-language comments and may not generalize to other Nigerian languages. In addition, the comments have 12 variables from 18 YouTube videos, and we used the column for the comments, and discarded the remaining columns.

This is because that is the column that is needed for the purpose of this study. A total of 1,412 replies were obtained from the comments, with a total of 7,852 likes for all 5,083 comments. During the conversion of YouTube comments to structure data, there are 10971 metric tonnes of words with 99.x% sparsity, which means 100% of the

time we will find zeros in the matrix. Comment 4085 *"If am sincere, Aare Dele did not speak specifics when asked direct questions on the economy. He sounded like someone that would run on vibes without"* attracted the highest likes with 47 likes.

The various scores for different sentiments were obtained, and 174 common words were removed because they were redundant, meaningless, and added no value to the comments [45]. In Table 2, there are 16 presidential aspirants who have declared their intentions. The youngest presidential aspirant is 38 years old and the oldest is 75 years, the average age is 58 years with a standard deviation of 11 years. The high value of this standard deviation shows the level of age variability among the 16 presidential aspirants. The p-value of 0.0000 at the 5% level of significance shows that there is a significant difference in age among the presidential aspirants, this also supports the claim about the variability. We are 95% confident that the average age of the presidential aspirants lies between 52 years and 64 years. Previous study showed that that national elections in Finland between 2011 and 2021 attracted attract relatively more young candidates, while candidate age also affects electoral selection [46]. In another study, presidential elections were among those with the highest median candidate ages and reported substantial differences between the youngest and oldest candidates within elections, supporting your observation of a relatively wide range (38–75 years) [47].

According to the public opinions on YouTube comments of all the 16 presidential aspirants in Fig. (5), most comments are *'negative'* and follow by *'positive'* comments, *'surprise'* has the lowest which means that the respondents are not shocked that the aspirants want to vie for the post. In Fig. (6), SA for *'neutral'* was included but no comments were classified into this category, though the graph was plotted to reveal the percentages of the SA. Fig. (7) shows the pie chart in percentages of the SA, most of the comments expressed *"negative"* sentiment, which accounted for about 20% of all the comments distribution. *"Positive"* is the next most expressed emotion and accounts for about 18% of all the comments. *"Trust"* shows the third greatest substantial sentiment of 11% among other opinions. *"Fear"* (10%), *"anger"* (9%), *"sadness"* (9%), *"anticipation"* (7%), *"disgust"* (7%), *"joy"* (6%), and *"surprise"* (3%).

Table 2: Brief information about the candidates.

S/N	Name	Current Party	Age (Years)	Gender	Region	Declaration Date
1.	Anyim Pius Anyim	PDP	61	Male	South East	6 th January 2022
2.	Yahya Bello	APC	46	Male	North Central	5 th January 2022
3.	Orji Uzor Kalu	APC	61	Male	South East	21 st January 2022
4.	Kingsley Moghalu	ADC	58	Male	South East	October 2021
5.	Dele Momodu	PDP	61	Male	South West	13 th January 2022
6.	Chukwuka Monye	-----	42	Male	South South	15 TH January 2022
7.	Bola Ahmed Tinubu	APC	69	Male	South West	10 th January 2022
8.	Omoyele Sowore	AAC	51	Male	South West	1 st March 2022
9.	Rochas Okoocha	APC	59	Male	South South	26 th January 2022
10.	Khadija Okunnu-Lamidi	-----	38	Female	South West	3 rd January 2022
11.	Sam Oluabunwa	PDP	71	Male	South East	18 th September 2021
12.	Doyin Okupe	PDP	69	Male	South West	5 th October 2021
13.	David Umahi	APC	58	Male	South East	11 th January 2022
14.	Bukola Saraki	PDP	59	Male	North Central	25 th November 2021
15.	Atiku Abubarka	PDP	75	Male	North East	3 rd March 2022
16.	Yul Edochie	----	40	Male	South East	May 2021

AAC - African Action Congress, ADC - African Democratic Congress, APC - All Progressives Congress, PDP - People's Democratic Party.

In Fig. (8), the number of times the words appear in the comments is shown in descending order. The most common word is "nigeria", followed by "will ", with the lowest word being "nigerian". We have removed words that do not appear up to 200 times to make the graph readable and presentable. Though there are some words that can be combined, like "nigerians" and "nigerian" we deliberately leave them out since they can suggest different things to the people who gave the opinions. The three presidential aspirants whose names appear are "tinubu", "sowore", and "orji or kalu", because the same presidential aspirant is going by the name "orji or kalu".

In Fig. (9), a word cloud is used to display the most common words [48-50]. This is used to show the common words in the YouTube comments of presidential aspirants for the 2023 election in Nigeria. The biggest word in the word cloud represents the word that appears most, while the smallest is the least frequent word in the comments. A high occurrence of the word "nigeria" shows that word "nigeria" is mentioned more than any other word in the comments. Other words like "people, "president", "will" and "man "also showed that they were significantly mentioned so many times in the YouTube comments.

Table 2 displays basic information about the 16 presidential aspirants for the 2023 election in Nigeria, we have one female and 17 males, with 3 candidates planning to run for the post as an independent candidate, 6 candidates are from the PDP, 5 candidates are from the APC, 1 candidate is from ADC, and 1 candidate is from AAC.

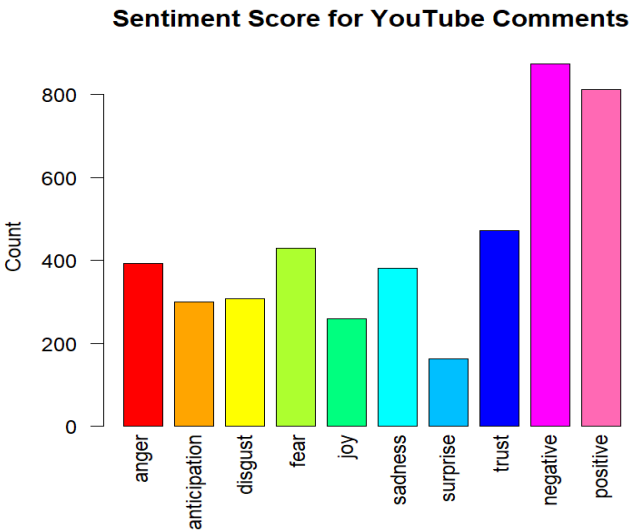


Figure 5: Bar Plot for the sentiment analysis in relationship to the frequency.

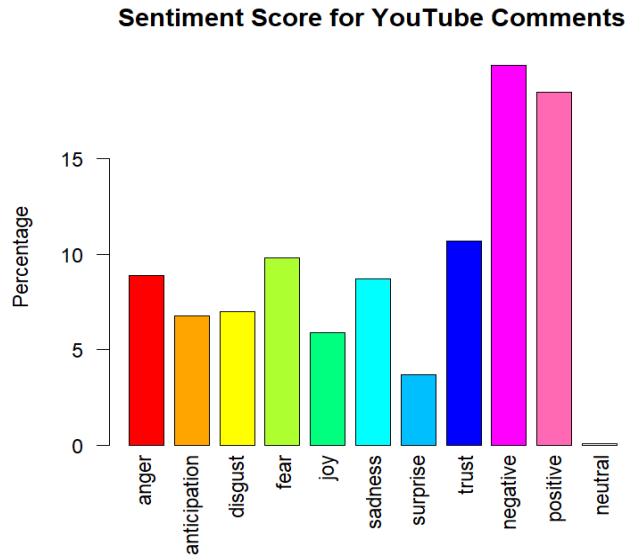


Figure 6: Bar Plot for the sentiment analysis in relation to their percentages, comments that are neutral are included here.

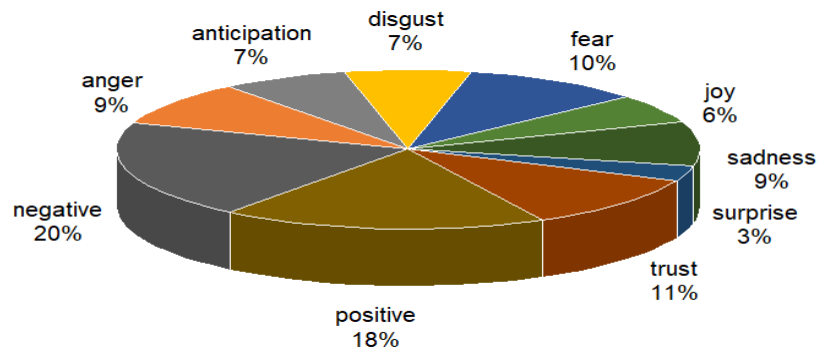
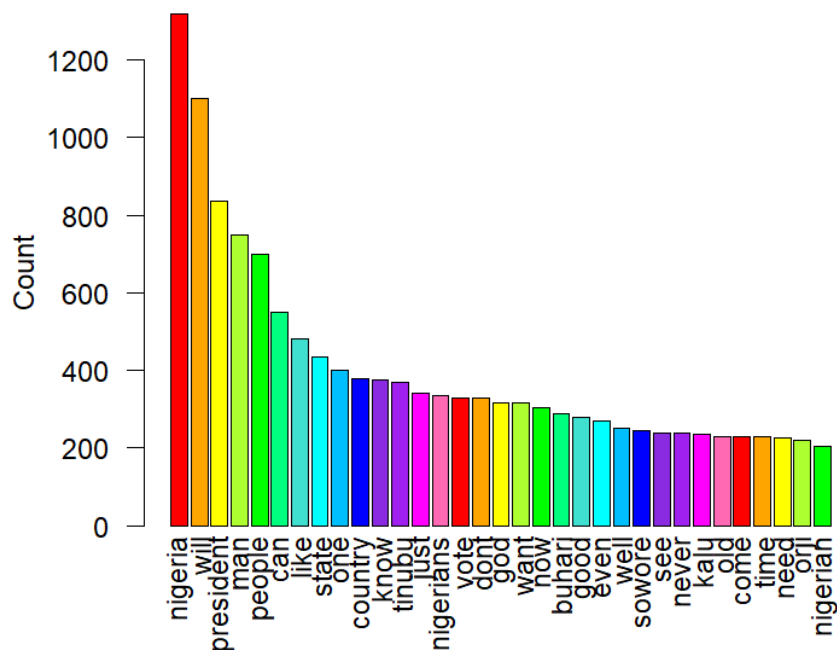
Pie Chart for the Sentiment Analysis**Figure 7:** Pie Chart for the sentiment analysis.**Bar Plot for the YouTube Comments****Figure 8:** Bar Plot for to show how frequent the words appear in the comments.**Figure 9:** Word cloud for the comments extracted from YouTube.

Table 3: Confusion matrix for classifier validation (n = 657).

Gold-Standard / Actual	Predicted Positive	Predicted Negative	Total
Positive	214	16	230
Negative	126	301	427
Total	340	317	657

Table 4: Classifier performance.

Metric	Formula	Result
Accuracy	$\frac{TP+TN}{N}$	78.39%
Precision (Positive)	$\frac{TP}{TP+FP}$	62.94%
Recall / Sensitivity (Positive)	$\frac{TP}{TP+FN}$	93.04%
Specificity	$\frac{TN}{TN+FP}$	70.49%
Negative Predictive Value	$\frac{TN}{TN+FN}$	94.95%
Balanced Accuracy	$\frac{\text{Sensitivity} + \text{Specificity}}{2}$	81.77%
Cohen's Kappa κ	Agreement beyond chance	0.5722

TP= True positive, TN=True Negative, N= Number of Comments, FP=False Positive, FN= False Negative.

In Table 3, the classifier correctly identified 214 of the 230 positive comments, it missed only 16 positive comments, indicating that the classifier was effective at detecting comments classified as positive by the gold standard. However, the classifier predicted 126 negative comments as positive. For the negative class, the classifier correctly classified 301 of 427 negative comments, while 126 were incorrectly classified as positive. Overall, 515 of the 657 comments were correctly classified. In Table 4, the classifier achieved an accuracy of 78.39%, with a precision of 62.94%, and recall of 93.04%. Specificity was 70.49%, while Cohen's κ was 0.572, indicating moderate-to-substantial agreement between the classifier predictions and the gold-standard annotations. Cohen's kappa of $\kappa = 0.5722$ indicates moderate inter-annotator agreement. In addition, it means that the two annotators achieved a level of agreement substantially above chance when independently classifying the 657 comments into sentiment categories. These results provide empirical evidence that the sentiment classifications used in the analysis were reasonably consistent with independently established human annotations.

5. Conclusion

The SA technique is a powerful tool for determining public opinion [51]. In this study, a complex SA of YouTube comments for 16 presidential aspirants for the 2023 election in Nigeria is presented. Complex SA is used to analyse the comments and achieve the purpose of the study.

Most of the comments by Nigerians on the aspirants are "*negative*," followed by "*positive*" comments. "*Surprise*" has the lowest percentage, which means that the respondents are not surprised that the aspirants want to vie for the post. The most common word is "*nigeria*" in the YouTube comments, and the three presidential aspirants ("*tinubu*," "*sowore*," and "*orji or kalu*") dominated the word cloud. Therefore, the findings reflect sentiment at the time of data collection and may not represent sentiment closer to the election. Overall, the validation results demonstrate that the classifier showed good sensitivity and satisfactory overall performance, with 78.39% accuracy, 62.94% precision, 93.04% recall, 75.09% F1-score, 70.49% specificity, and $\kappa = 0.572$, while the moderate inter-annotator agreement supports the consistency of the human-annotated gold-standard labels.

This study has several limitations. First, there was substantial variability in the ages of the presidential aspirants, which may influence comparisons based on age-related characteristics. Second, comments were unavailable for some YouTube videos because the comment function was disabled, limiting the completeness of the available public engagement data. In addition, the 'sreplytoanotheruser' variable was unavailable, preventing the construction of a user-reply network for network analysis. Finally, the comments were collected on a single date (18 March 2022), well before the 2023 election. Political sentiment may change over time in response to electoral campaigns and other political developments; therefore, the findings reflect sentiment at the time of data collection and may not represent sentiment closer to the election.

Future studies should move beyond single-platform polarity classification by developing multilingual and multimodal transformer-based frameworks that integrate YouTube comments with other social media data. Incorporating aspect-based sentiment analysis, emotion detection, topic modeling, bot identification, and explainable artificial intelligence techniques would provide deeper insights into the dynamics of political discourse and the influence of online sentiments on electoral processes in Nigeria and other emerging democracies. That comparison with official election results could provide an additional external perspective. Future studies could also compare candidate-level sentiment outcomes with official election results to examine the association between social-media sentiment and electoral outcomes. Such analysis could provide an additional external validation of sentiment patterns while extending the scope of the present study.

Conflict of Interest

There is no conflict of interest among the authors.

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Data Availability

All the data are available upon request from the corresponding author.

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