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Sentiment Analysis of Twitter Discourse on the 2023 Nigerian General Elections

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ABSTRACT: *Sentiment analysis entails discerning whether text conveys positive, neutral, or negative sentiments to ascertain the mood of the public concerning a given entity. This method relies on natural language processing, computational linguistics, and text analysis to identify, extract, and methodically analyze affective and subjective data. The 2023 Nigerian presidential election holds immense significance for the nation, determining its leadership for the subsequent four years. Consequently, comprehending public sentiment regarding the electoral process becomes paramount. This study sought to gauge public sentiment concerning the 2023 Nigerian General Elections by analyzing tweets related to candidates and their political parties. Leveraging three machine learning (ML) techniques—SVM, RF, and XGBoost—we aimed to categorize tweets as negative, positive, or neutral. Our dataset comprised a substantial volume of tweets, meticulously pre-processed to eliminate irrelevant content and noise. Results showcased the outstanding performance of RF and XGBoost in tweets classification and sentiment identification about the electoral process with the highest accuracy (93%) and precision (96%), occurring on neutral opinions. These results findings offer crucial insights into public opinion regarding candidates, their political parties, and the electoral procedure, benefiting researchers, political analysts and decision-makers alike. It suggests that 43% of the electorate expressed neutral sentiments about the elections, while 33% expressed positive sentiments, such as optimism about the electoral process, support for specific candidates, satisfaction with the results of the election, or excitement for taking part in democracy. Meanwhile, 24% of the electorate expressed negative sentiments, such as dissatisfaction with political candidates, criticism of the electoral processes, worries about fairness, or skepticism about the outcome. This research underscores the significance of sentiment analysis in comprehending public opinion and its potential contributions to political discourse.*
KEYWORDS: sentiment analysis, twitter discourse, 2023 Nigerian general elections

INTRODUCTION

In the modern age, social media platforms have become vital channels for political discourse, allowing citizens to express their opinions, sentiments, and concerns. In particular, Twitter (now known as X) has emerged as a powerful tool for political communication and engagement, allowing users to share their views on various socio-political events, including elections. Like many others globally, the 2023 Nigerian General Elections garnered significant attention and discussion on Twitter. These elections held immense importance for Nigeria, a country known for its complex socio-political landscape, diverse population, and historical significance. As with any major political event, the discourse surrounding the Nigerian General Elections on Twitter was multifaceted, reflecting various opinions, emotions, and perspectives.

Sentiment analysis within the field of natural language processing (NLP) provides a systematic approach to analyzing and understanding the sentiments expressed in textual data. Researchers can gain valuable insights into public opinion dynamics, political discourse, and voter sentiment during electoral processes by employing sentiment analysis techniques. Sentiment analysis has been applied to express sentiments in electronic word of mouth (eWOM) on e-learning (Obot et al., 2025), analysis of online product reviews (Asuquo et al., 2023; Loukili et al., 2023; Elzeheiry et al., 2023) and election prediction (Chauhan et al., 2023; Jubba et al., 2023). This study examines the sentiment analysis of Twitter discourse surrounding the 2023 Nigerian General Elections. We aim touse NLP techniques to break down each tweet's text into individual sentences. Then apply sentiment analysis techniques to those sentences to classify and aggregate them into one of the sentiment categories based on the sentiment polarity that found during the analysis. Furthermore, we leverage TextBlob, a well-known Python sentiment analysis and text processing library to categorize tweets as positive, neutral, or negative categories, providing a nuanced understanding of the sentiment landscape and machine learning(ML) techniques to analyze and classify sentiments. By conducting this analysis, we seek to advance knowledge about political discourse on social media platforms and African elections specifically. Our findings offer valuable insights for political analysts, policymakers, and stakeholders interested in understanding public opinion dynamics and the role of social media in shaping electoral outcomes.

Random Forest (RF), Extreme Gradient Boost (XGBOOST), and Support Vector Machines (SVM) are algorithms utilized for the sentiment classification task. XGBoost is a powerful ML algorithm that is frequently applied to classification tasks because of its effectiveness and speed (Asselman et al., 2023). By using cross-validation techniques to prevent over-fitting, XGBoost can be effective even with small datasets (Asselman et al., 2023;Fatima et al., 2023). RF is an ensemble method that combines several decision trees to generate predictions. It is reliable and effective for handling text as well as other types of structured and unstructured data (Pimpalkar et al., 2024; Kigo et al., 2023). When there are numerous features, like words or phrases, in a text analysis, SVM performs exceptionally well in handling high-dimensional data, which makes it ideal for sentiment analysis (Rao, 2024; Chang et al., 2023).

The rest of the paper is arranged as follows. In Section 2, relevant sentiment analysis works are reviewed. The methodology used for this study, the suggested framework, and an explanation of the algorithms and evaluation metrics employed are all covered in Section 3. In Section 4, the classifiers' performance is evaluated and the presented results are compared with existing literature, demonstrating the classifiers' efficacy in polarity classification of sentiments into neutral, positive, and negative categories. The concluding remarks and recommendations for further work are presented in Section 5.

RELATED WORKS

To forecast significant decisions from online social media platforms, Chauhan et al (2021) offer and evaluate the effectiveness of many volumetric, sentiment, and social network methodologies. Individual opinions are crucial in helping identify some important choices. This survey report describes sentiment analysis methods and attempts to highlight the role that scholars have had in using social media content to forecast election outcomes. This report also identifies unresolved problems in sentiment analysis and research difficulties linked to election outcome prediction. Moreover, this study makes some recommendations for potential future developments in the domain of electoral prediction based on social media materials like Facebook and Twitter.

Using sentiment analysis and Twitter data, Yavari et al. (2022) find that the ratio of positive to negative message rates is a useful signal for election prediction. After that, the aging estimation approach is used to project the values of this indicator for future periods. High degrees of accuracy can be achieved in predicting indicator values and, ultimately, election outcomes, according to experiments conducted over four months on Twitter data related to the 2020 US presidential election.

The goal of Ali et al. (2022) was to emphasize how crucial it is to perform sentiment analysis for every post that was made in real-time, as well as the ones that are currently inaccessible, to ascertain the actual feelings of the opinions at the moment of an occurrence. The study was able to ascertain public opinion regarding the 2020 US presidential candidates by examining 7.6 million tweets sent between October 31, 2020, and November 9, 2020. Using a cutting-edge method, the researchers first located user profiles in the system that were subsequently removed from Twitter. This method makes it possible to track the opinions people have for each presidential candidate across a range of tweet categories and users, including visible, deleted, suspended, and inaccessible accounts and tweets. The study provides important insights into the variations by comparing the sentiment scores that were computed for different groups. Most significantly, the researchers demonstrate that tweets that were removed were more positive about Donald Trump and more supportive of Joe Biden when they were posted in the run-up to the election date. Additionally, a Twitter account would tweet more supportive things about Joe Biden the older it was.

A sentiment analysis method that works best is proposed by Hananto et al. (2023) for the Indonesian presidential election on Twitter. This study examined public perceptions of trends in presidential candidates using comparisons of the support vector machine (SVM), K-Nearest Neighbor (K-NN), and Naïve Bayes (NB) classification algorithms. To determine which algorithm is more accurate, comparisons are done. This study is expected to provide the public with data and references regarding the trends of presidential candidates in the upcoming election. The data collected comprises 9966 tweets from September 17, 2022, the second week of the campaign, about the president and presidential contenders. The test results showed that, with an accuracy rate of 79.57%, the SVM algorithm outperforms K-NN and Naïve Bayes. The study's findings yield the best and most efficient algorithm for dividing comments about the 2024 presidential candidate trend into positive and negative categories.

Using a semi-supervised methodology, Macrohon et al. (2022) conducted a sentiment analysis on tweets during the Philippine presidential election. This study analyzes sentiment in tweets written in both Tagalog and English using a simple classifier that is semi-supervised. The tweets from the hotly contested fight between the departing vice president and the son of the country's former dictator were used in this study, which focused on the Philippines and saw social media play a significant role in both candidates' campaigns. To categorize English and Tagalog tweets into three polarities: positive, neutral, and negative, these tweets were subjected to natural language processing (NLP) approaches for analysis, annotation, and training. Outperforming earlier studies employing Twitter data from the Philippines, with 30% of the data unlabelled, 84.83% accuracy was obtained by Self-Training with Multinomial Naïve Bayes as the basis classifier. Hare et al. (2023) attempted to analyze the attitudes of Indian citizens during the 2019 Lok Sabha election. Because this is an unsupervised task, the researchers have used Transfer Learning to create an automatic tweet analyzer. The study handled the textual data from tweets using the Term Frequency Inverse Document Frequency (TF-IDF) approach and the Linear Support Vector Classifiers method in the MLmodel. The researchers improved the model's capacity to handle the sarcastic tweets that some of the users posted—a feature that no other researcher in this field has yet to take into account.

Baharuddin et al. (2022) attempt to show whether Twitter analysis can anticipate and identify contenders for the Indonesian presidential election of 2024. This research was done far in advance of the election. Sentiment analysis and word searches on Twitter data were employed simultaneously as two modes of analysis to minimize the gaps and utopian attitudes in the data. In this work, descriptive content analysis is combined with a quantitative methodology. The information was gathered from Twitter social media, where official accounts and 2024 presidential election-related issues were the main focus of Twitter Search. First, the data collection and search were altered to match the pattern of poll results appearing in Internet news. The candidates' names to be looked for on Twitter are modified based on the poll's trend. The Nvivo 12 Plus analysis program is also employed by the analysis tool. Three possible candidates for the 2024 election were successfully identified by this study: AniesBaswedan, GanjarPranowo, and Prabowo Subianto. There is a correlation between the mapping of possible candidates and newspaper opinion poll findings. Based on these results, predictions may be made and an alternative to the poll approach can be found by utilizing the information and data on Twitter. This study's shortcoming is its restricted time frame.

Eze et al, (2023) suggested Sentiment Analysis and Perception Mining of Political Socialization Among Twitter Users in the 2023 Nigerian General Election. This study examines the political utility and application of Twitter by utilizing sentiment analysis and content analysis (textual) to look at the online communication patterns of Nigerian voters in the lead-up to the 2023 Nigerian General Elections (NGE23) and forecast results. Information and communication technology (ICT) specialists were hired to determine content analysis for the three major Nigerian languages, Igbo, Hausa, and Yoruba, while NB, SVM, and Random Forest (RF) were used to determine sentiment analysis for English tweets.

Opinion mining, which is a popular experiment that gathers opinions from the public, is supported by sentiment analysis. Twitter has become popular and is an important tool for examining public opinion on elections and other points of discussion. Many state-of-the-art language models have been utilized formerly to predict election results. The unexpectedly fascinating results of Nigeria's recent presidential election have brought attention to the upcoming Lagos State gubernatorial contest. Wusu et al. (2023) proposed using Twitter data Google's Bidirectional Encoder Representations from Transformers (BERT) model was used to analyze the sentiment surrounding the governorship election in Lagos State, Nigeria. Using carefully chosen search queries, 800,000 private and public tweets about the three leading candidates running for governor of Lagos State were scraped from Twitter. To prevent noise and irregularities, the tweets were pre-processed, and the pre-processed tweets were fed into the BERT model, which had already been trained and adjusted. To ascertain the public's perceptions of the candidates, the outcome was examined. Additionally, the candidates' social networks were displayed, and the impact of various learning rates (LR) on the parameters was taken into account. Under a range of LRs and epoch sizes, the BERT model's maximum performance was 91% F1 measure,88% precision, and 92% recall. The LR at 1e-7 performed the best, according to the results as well. Furthermore, the accuracy increases with larger epoch sizes and decreases with smaller LR. The created BERT model applied to the public's tweet indicated that the election will be a two-party struggle between the Labor Party and the All Progressives Congress party, upending the current quo. The results of the experiment demonstrated how sentiment analysis and other NLP activities can help with social media environment knowledge. The outcomes also showed the extent to which each candidate influences the election's outcome. It is concluded that political parties can benefit from information provided by sentiment analysis and other language models in predicting election outcomes.

The study by Jimada, (2023) looks at how political candidates and their supporters use social media for campaigns, particularly how they use it to propagate hate and dangerous messages in Nigeria in 2023. Critical studies employing qualitative methods and analysis are part of the study. It examines how violence in a shattered Nigerian society is fuelled by hate speech and false information. Nigerian society has a history of developing fault lines and cleavages. Over time, ethnic and religious divisions have formed the basis of these fault lines. The possibility of a peaceful, orderly, and violence-free election process is greatly reduced when competing interest groups openly display their differences during elections, which are frequently linked to power struggles.

Abubakar and Omowunmi (2023)investigate the media engagement tactics employed by the three front-runners for the presidency in Nigeria's general election. Using appraisal theory as a guide, the study looks at how the candidates use language to negotiate their interpersonal posture and persuade the audience. The Nigerian Economy Summit Group (NESG) conducted interviews with presidential candidates on January 13 and 16, 2023, under the theme "Dialogue with Presidential Candidates on Nigerian Economy." The study used a descriptive survey to ascertain the candidates' approaches to evaluating Nigeria's economic circumstances and other matters. The findings showed that the applicants employed a range of engagement strategies, including asserting, rejecting, and describing the evaluation's aims. The study emphasizes how crucial it is for politicians to effectively engage the public during media discourse by utilizing appropriate language and communication techniques. The study's findings will add to the body of knowledge already available on political engagement and communication tactics and offer practical advice for aspiring politicians and campaign slogans.

In Dii (2023), the impact of voter disposition on the Nigerian presidential election result is discussed. The objective was to look at voter views and how they impacted the presidential election. Its research methodology combined the qualitative secondary research approach with the grounded theory method of inquiry. RCT, or rational choice theory, served as the foundation for the paper's theoretical framework. Effective voter education and the pledge to use technology, such as the Independent National Electoral Commission's (INEC) Voter Enrolment Device (IVED), the Bimodal Voter Accreditation System (BVAS) for both voter accreditation and e-transmission of results for collation, and the INEC results viewing (IReV) portal, which will enable the public to view polling unit results in real-time, were found to have significantly increased voter participation. Voter disposition significantly affected the outcome of the presidential election, yet INEC broke its word and changed the regulations mid-exercise. To ensure that all technologies are used for conducting and announcing election results, it was proposed that the 2022 Amended Electoral Act be reexamined. Additionally, it was proposed that diaspora voters in Nigeria's democratic system be permitted to use e-voting technology, which uses electronic ballot sheets to permit voting from any location as long as one is legally registered.

The results of sentiment analysis for low-resource African languages using the Twitter dataset in Hausa NLP were presented by Abdullahi et al. (2023) utilizing SemEval-2023 Task 12: Leveraging African Low Resource TweetData for Sentiment Analysis, a shared task. Subtasks A and B featured multilingual sentiment classification using subtask A's tracks, subtask C involved zero-shot sentiment classification, and subtask A's 12 tracks comprised a monolingual sentiment classification task. The results and deductions from tasks A, B, and C were discussed. The goal was to implement pre-trained Afro-xlmr-large, AfriBERTa-Large, Bert-base-arabic-camelbert-da-sentiment (Arabic-camelbert), Multilingual-BERT (mBERT), and BERT models for sentiment analysis of 14 African languages. Twitter data with few resources was used to do this. The datasets used for these subtasks were the industry standard multi-class labelled Twitter datasets from these languages. The results demonstrated that the Afro-xlmr-large model performed better than the other models in most of the language datasets. The Nigerian languages Hausa, Igbo, and Yoruba performed better than other languages due to the greater amount of data in the languages.

The advancement of technology in the field of digital transformation has led to a significant surge in the usage of social media and the Internet. These platforms are widely used by people to express their ideas, opinions, and life experiences. Any organization can benefit from analyzing this data since it helps it better understand the needs of its clients. Sentiment analysis is a comprehensible method of interpreting the textual information's emotions and identifying whether those emotions are positive or negative. Dhola and Saradva (2021) provided experimental results that illustrated the comparative performance analysis of different classification algorithms and described the data cleaning and preparation procedure for sentiment analysis. Various ML techniques such as SVM, Multinomial NB, and deep learning techniques such as BERT, and Long Short-Term Memory(LSTM) for sentiment analysis were analyzed.

Nassif et al. (2021) conducted a comprehensive comparison between various shallow learning classifiers, deep learning models, and their hybrids, for sentiment analysis of Arabic reviews. The comparison also includes more recent models, such as the transformer architecture and the araBERT pre-trained model. The multi-dialect Arabic hotel and book review datasets included in this study were among the largest publicly available datasets for reviews written in Arabic. The results demonstrated that for binary and multi-label classification, deep learning performed better than shallow learning. The accuracy and F1 score of both deep and shallow learning approaches were examined. RF was the most effective shallow learning technique, followed by AdaBoost and Decision Tree (DT). When the transformer model was augmented with araBERT, it performed better than the deep learning models; however, when the default embedding layer was used, the deep learning models performed equally.

A real-time sentiment analysis system for social networks that integrates textual and visual data was developed by Shixiao et al. (2023) to increase accuracy. They evaluated the system using measures like F1-score, accuracy, precision, and recall using CNN, LSTM, and SVM networks. The system is appropriate for a variety of applications, including social media monitoring and marketing analysis, because it can handle multimodal data with high accuracy in real-time. However, properly training the modelsrequires more training data because it struggle with noisy and ambiguous data, including irony and sarcasm.

Shan (2023) proposed a Convolutional Neural Network - Bidirectional Gated Recurrent Unit (CNN-BiGRU) based method for sentiment analysis of social network text in a big data environment. To create word vectors and represent word relationships, the method uses dependency syntax trees. Using numerous convolution kernels of different sizes in a CNN, sentiment characteristics of various granularities are retrieved. The method was evaluated using a Chinese natural language processing dataset source from the Chinese NLP Corpus project on GitHub. To enhance analysis performance, the proposed approach employs the Dropout method and Adam optimizer. The CNN-BiGRU model achieved notable sentiment analysis performance, with an accuracy of 94.09%, precision of 95.13%, recall of 92.87%, and an Area under the ROC Curve(AUC)of 0.953. Despite its success, the method only categorizes text sentiment into positive and negative polarities, lacking finer-grained sentiment identification and deeper sentiment analysis, such as distinguishing between positive, neutral, and negative sentiments, or further categorizing into emotions like pleasure, anger, sorrow, and joy.

Merayo et al. (2023) presented a novel hybrid deep learning model to identify polarity levels in tweets posted in Spanish on Twitter by combining convolutional and LSTM layers. The accuracy of their model is far higher than that of existing methods, with accuracies of roughly 76% for three polarities (positive, negative, and neutral) and 91% for two polarities (positive and negative). Nevertheless, the study does not evaluate the model's robustness and suitability across various Spanish datasets, nor does it explain how the classifier handles irony or ambiguity in Spanish tweets.

Varghese et al. (2021) provide an overview of sentiment analysis on social media data for identifying anxiety or despair using a range of artificial intelligence approaches. The study investigates the application of sentiment analysis to social media data in several scenarios through the use of hashtags. Following preprocessing and feature extraction, sentiments are categorized using a variety of classification algorithms according to their polarity or sentiment score. Numerous deep learning or machine learning (ML) approaches are used in the analysis or classification process. The results suggest that deep learning algorithms for multi-class classification provide accurate sentiment categorization with texts, emoticons, and emojis when compared to alternative combinations of classification algorithms. Nevertheless, the study did not use other datasets for the detection of depression (such as biometric data, voice signals, facial expressions, and EEG signals). Furthermore, several algorithms to assess accuracy values under various circumstances and using various datasets are not combined in this work.

Sudarsa et al. (2018) introduced a sentiment analysis system designed to classify sentences and product opinions sourced exclusively from Twitter data. The system utilized NB and SVM algorithms. NB achieved an accuracy of 88.2%, whereas SVM achieved 80%accuracy.

Khan et al. (2023) proposed ElecBERT, an election-focused sentiment analysis model tailored for election-related tweets. ElecBERT, which is based on the BERT language model, was refined using two datasets with millions of labeled tweets each: ElecSent-Multi-Languages and ElecSent-English. On both datasets, the model outperformed more conventional ML models such as SVM, NB, and XGBoost, obtaining high accuracy and F1 scores. The study's conclusions offer insightful information about sentiment analysis in election contexts, with potential uses in political analysis, social media administration, and policymaking. ElecBERT's success is tempered by limitations: trained solely on 2020 US Presidential Election data, relying on automated sentiment labeling (VADER) without manual review. Future improvements may involve integrating diverse election data, exploring alternative pre-trained models like PoliBERT, and enhancing the model's complexity to capture nuanced linguistic features such as sarcasm and irony.

To use Twitter data to study popular opinion on the 2023 Nigerian presidential election, Olabanjo et al. (2023) created a Natural Language Processing framework). The three well-known candidates, Atiku Abubakar, Peter Obi, and Bola Tinubu, were the subject of two million tweets, both from public and private accounts. Following the preprocessing of the dataset, three machine learning models were used for sentiment analysis: the Linear Support Vector Classifier (LSVC), the Bidirectional Encoder Representations from Transformers (BERT), and the Long Short-Term Memory (LSTM) Recurrent Neural Network. In terms of accuracy, precision, recall, AUC, and f-measure, the sentiment models performed differently. Tinubu possessed the greatest circle of active friends, Atiku gathered the most followers, while Peter Obi received the most impressions overall and favourable feedback.

To choose the most informative features from Chinese microblogs for sentiment classification, Zolotareva et al. (2022) used a genetic algorithm. The study highlights that feature selection can enhance sentiment classification performance, though it faces challenges due to the high dimensionality of the feature space. Additionally, future research will explore the integration of deep learning-based feature extraction techniques in sentiment analysis.

To classify tweets, Saravana et al. (2013) built a rule-based sentiment analysis system using a sentiment lexicon and a predetermined set of rules. The study demonstrates that rule-based sentiment analysis can achieve acceptable accuracy levels. However, it may encounter challenges in handling intricate data and might necessitate manual adjustments. The researchers also investigated the application of machine learning techniques in sentiment analysis.

METHODOLOGY AND EXPERIMENTAL SETUP

This is a summary of the approach taken to develop the hybrid lexicon and machine learning based framework for analysing sentiment. The Twitter API was used to acquire Twitter data and English tweets were extracted with the help of the Tweepy library. Before the sentiment analysis exercise, data cleaning and pre-processing was done on the text data to filter out and remove noisy from the data, which makes it easier to convert unstructured data into a readable format. The process entails breaking up the text into individual tokens or words, reducing the tokens to their simplest form through lemmatization or stemming, eliminating stopwords that don't add much to the sentiment analysis, and eliminating special characters like @, #, $, *, ", unwanted blanks, punctuations, and hypertext markup language (HTML) tags. Processed data in a format that can be used as input for tasks involving sentiment analysis is the end result of the entire procedure.

A natural language processing (NLP) Python package called TextBlob with numerous sentiment analysis features, was later implemented. A well-known Python package for sentiment analysis and text processing is called TextBlob. It offers a straightforward API that allows text to be subjected to sentiment analysis by simply assigning subjectivity and polarity scores. On a scale from -1 to +1, polarity indicates the sentiment (negative or positive) expressed. A negative emotion is represented by a score of -1, a neutral emotion by 0, and a positive emotion by 1. Subjectivity is a measure of the text's level of objectivity or subjectivity. Subjectivity, on the other hand, quantifies the extent of either objective or subjective content in a text and is also measured on a scale from 0 to 1, where 1 represents a subjective statement and 0 an objective statement. TextBlob uses the Pattern Analyzer to compute subjectivity and polarity. In the first approach, TextBlob analyzes patterns for sentiment using the Pattern library. The Pattern library uses a lexicon of adjectives and their manually tagged scores to determine the sentiment polarity of each word in a text. By averaging the polarity scores of each word in the passage, TextBlob determines the overall polarity of the text.

Subjectivity and polarity scores were the inputs, and the generated sentiment was the output in the labelled dataset used by the machine learning algorithms. To train and test the model, the dataset consisting of 3046 tweets was divided in an 8:2 ratio. The suggested combined lexicon-ML architecture for sentiment analysis is shown in Fig. 1. The machine learning algorithms XGBOOST, SVM, and RF were employed for the sentiment classification task.

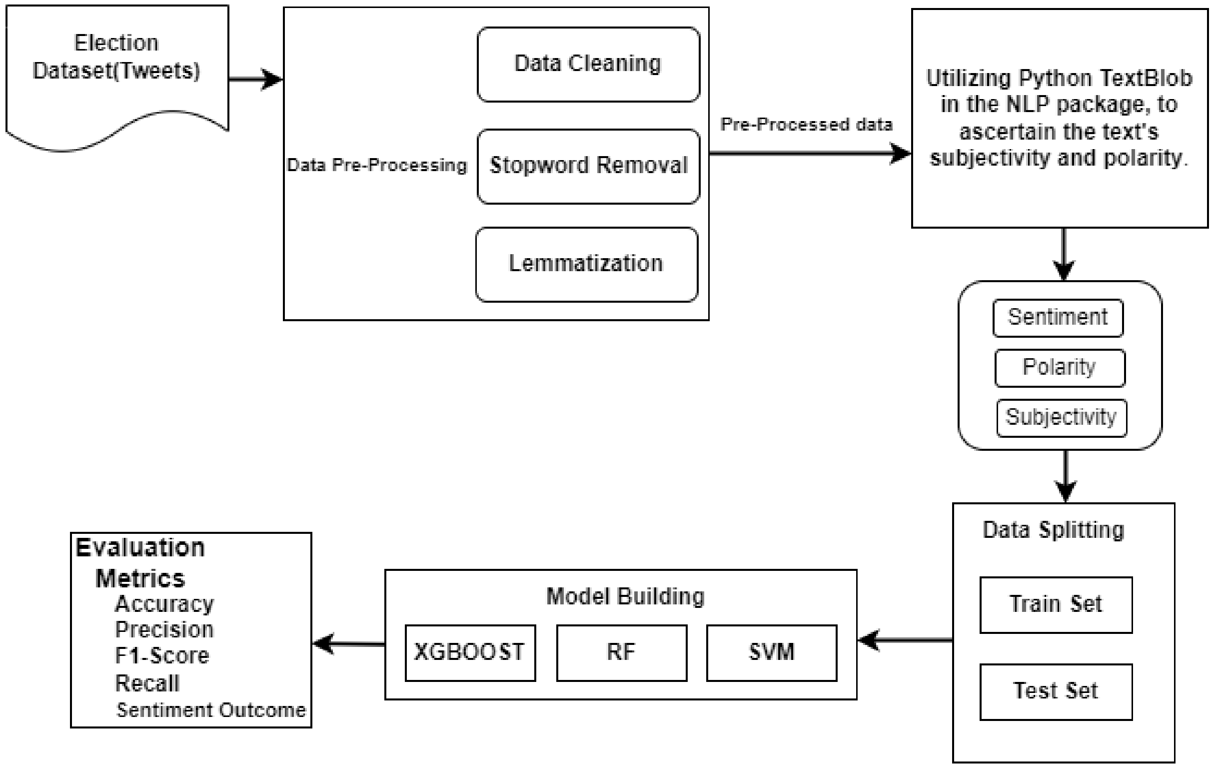

Figure 1: Proposed combined lexicon-ML architecture for sentiment classification

Several metrics, including precision, recall, F1-score, and accuracy, were used to assess the performance of the ML classifiers. The equations (1) to (4) present these metrics. True Positive (TP) denotes comments that are both observed and predicted to be positive, while True Negative (TN) denotes comments that are both observed and predicted to be negative. False Positive (FP) describes comments that are predicted to be positive but are actually observed to be negative, and False Negative (FN) describes comments that are observed to be positive but are actually predicted to be negative by the classifiers.

$$Precision = {}^{TP}/_{TP + FP} \tag{1}$$

$$Recall = {}^{TP}/_{TP + FN} \tag{2}$$

$$F1\ score = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{3}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

RESULTS AND DISCUSSION

In TextBlob, the NLP processing package's class distribution of neutral, negative, and positive sentiment is shown in Fig 2. TextbBlob presents sentiments (negative, neutral, and positive), subjectivity, and polarity. Figure 2 indicates that 24% of the tweets had negative sentiments 33% had positive sentiment and 43% had neutral sentiment. The result reveals that the largest portion of the tweets falls into the neutral category, indicating that a significant number of tweets did not express clear positive or negative emotions regarding the elections, which may include factual updates or opinions that are neither strongly positive nor negative. Negative sentiments could include dissatisfaction with political candidates, criticism of election processes, concerns about fairness, or skepticism about the outcome. Positive sentiments may include support for particular candidates, optimism about the electoral process, satisfaction with election outcomes, or enthusiasm for participating in democracy. The Python codes used for the sentiment analysis of the general election tweets can be found on GitHub.com (https://github.com/kingattai/Election-Sentiment-Analysis). Fig. 3 displays the sample tweets as well as the sentiment polarity and TextBlob subjectivity and polarity scores. Next, the sentiments were converted into the following encoded format for ML algorithms to easily classify them: (Positive sentiment=2, Negative sentiment=1,Neutral sentiment=0).

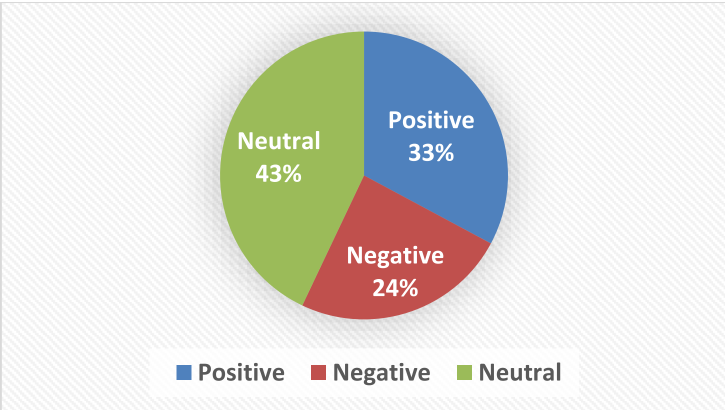

Figure 2: Distributing the election tweets by class

	A	B	C	D	E
1	Tweets	Cleaned_Tweet	Sentiment	Subjectivity	Polarity
2	CAN Decries Naira Short	decries naira shortage u	Neutral	0	0
3	Zamfara Commissioner I	zamfara commissioner	Neutral	0	0
4	This election is betweer	election po atiku apc tir	Negative	0.35	-0.1
5	This jungle don over ma	jungle mature	Positive	0.1	0.1
6	Corrupt politicians are n	corrupt politicians movi	Negative	1	-0.5
7	Kwankwaso Rejects Pre-	kwankwaso rejects pre	Neutral	0	0
8	Please show Kwankwas	please show kwankwas	Neutral	0	0
9	NNPP has locked Kwank	nnpp locked kwankwas	Neutral	0	0
10	Even all the crowd in kw	even crowd kwankwasc	Neutral	0	0
11	Kwakwanso thought gov	kwakwanso thought go	Positive	0.3	0.1
12	Stop putting up this bigc	stop putting bigot jare r	Neutral	0	0
13	That's Great, but please	great please open inec	Positive	0.45	0.333333333
14	He has forgotten so soo	forgotten soon peter hc	Neutral	1	0
15	And channels had to use	channels use picture ob	Neutral	0	0
16	Loser should hang up hi:	loser hang red cap	Neutral	0	0
17	They locked it but some	locked someone else h	Neutral	1	0
18	Locker of the North	locker north	Neutral	0	0
19	Atiku locked North Tinu	atiku locked north tinut	Positive	1	1
20	Last last you will tell yo	last last tell supporters	Neutral	0.066666667	0
21	Tinubu Promises To Rec	tinubu promises recruit	Positive	0.3	1
22	Somebody who is NOT k	somebody best nigeriar	Positive	0.325	0.375
23	BOLA AHMED HAS THE B	bola ahmed best campa	Positive	0.43125	0.3625

Fig. 3. Sample tweets

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The sentiment dataset that has been transformed for sentiment class predictive modeling is displayed in Figure 4. The following are the parameters of the multi-class classification algorithms:Subjectivity, Polarity, and Sentiment(X(Input Variable) = Y(Classes) (0,1,2)

	A	B	C
1	Subjectivity	Polarity	Sentiment
7	0	0	0
8	0	0	0
9	0	0	0
10	0	0	0
11	0.3	0.1	2
12	0	0	0
13	0.45	0.333333333	2
14	1	0	0
15	0	0	0
16	0	0	0
17	1	0	0
18	0	0	0
19	1	1	2
20	0.066666667	0	0
21	0.3	1	2
22	0.325	0.375	2
23	0.43125	0.3625	2
24	0.576388889	-0.056944444	1

Fig. 4. Transformed sentiment dataset

Tables 1-3 and Fig. 5 present the performance of RF, SVM, and XGBoost. Table 1 shows that for sentiments that are neutral, negative, and positive, respectively, RF produces a 93% prediction accuracy with precision (96%, 94%, 90%), recall (95%, 91%, 93%), and F1-score (96%, 92%, 92%).For neutral, negative, and positive sentiments, Table 2 shows that the SVM classifier has an average accuracy of 89%, along with precision values of 93%, 86%, and 87%, recall values of 89%, 88%, and 92%, and F1-score values of 91%, 87%, and 89%.Finally, Table 3 shows that the XGBOOST classifier has an average accuracy of 93% along with precision (96%, 94%, 89%), recall (96%, 89%, 93%), and F1-score (96%, 91%, 91%) for neutral, negative, and positive sentiments respectively. In conclusion, both RF and XGBoost classifiers achieved the highest accuracy of 93%, while SVM achieved an accuracy of 89%. RF and XGBoost classifiers generally outperformed SVM in precision across all sentiment categories. RF and XGBoost achieved higher precision for neutral and negative sentiments compared to SVM. RF classifier achieved higher recall for neutral and positive sentiments compared to SVM and XGBoost. However, XGBoost achieved the highest recall for negative sentiments. RF and XGBoost generally achieved higher F1 scores compared to SVM, especially for positive and neutral sentiments.

Table 1. RF performance

	Precision	Recall	f1-score	support
0	0.96	0.95	0.96	258
1	0.94	0.91	0.92	161
2	0.9	0.93	0.92	191
accuracy			0.93	610
macro avg	0.93	0.93	0.93	610
weighted avg	0.93	0.93	0.93	610

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Table 2. SVM performance

	Precision	Recall	f1-score	Support
0	0.93	0.89	0.91	258
1	0.86	0.88	0.87	161
2	0.87	0.92	0.89	191
accuracy			0.89	610
macro avg	0.89	0.89	0.89	610
weighted avg	0.89	0.89	0.89	610

Table 3. XGBOOST performance

	Precision	Recall	f1-score	support
0	0.96	0.96	0.96	258
1	0.94	0.89	0.91	161
2	0.89	0.93	0.91	191
accuracy			0.93	610
macro avg	0.93	0.92	0.93	610
weighted avg	0.93	0.93	0.93	610

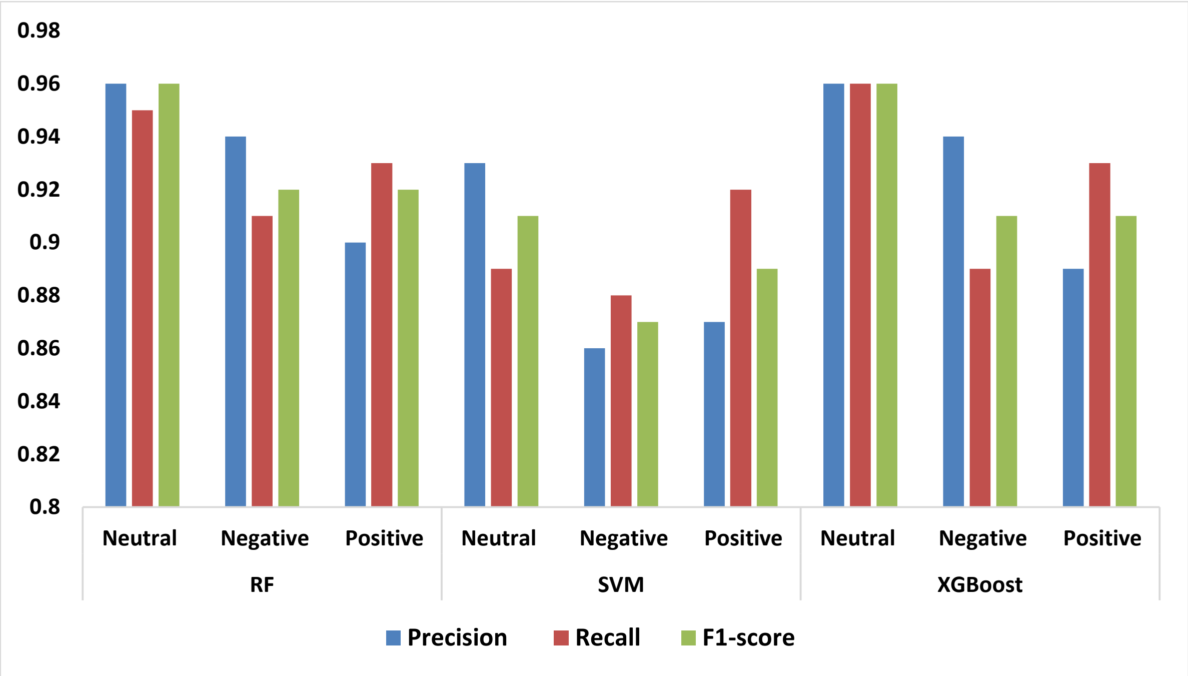

Fig 5.Performance Metrics across ML models

RF and XGBoost algorithms achieved an impressive accuracy of 93%, demonstrating the efficacy of ensemble learning methods in accurately classifying sentiment even with a small dataset. The high accuracy shows that, despite possible noise and variability in the data, the RF and XGBoost models are reliable and able to capture the subtleties of sentiment expressed in the tweets.

Hananto et al. (2023) reported an accuracy of 79.57% with SVM, whereas Sudarsa et al. (2018) reported an accuracy of 88.2% using Naïve Bayes. These findings suggest that RF and XGBoost models perform better in sentiment analysis than these conventional ML algorithms. Using a more sophisticated model, CNN-BiGRU, Shan (2023) obtained a marginally higher accuracy of 94.09%, demonstrating the potency of deep learning techniques in identifying intricate patterns in text data. Nonetheless, given the ease of use and effectiveness of RF and XGBoost, particularly when working with a limited dataset, our study's performance with these algorithms is still comparable.Naïve Bayes was found to have an accuracy of 84.83% by Macrohon et al. (2022). The results of our study, even with limited data, clearly surpass this baseline and show that ensemble learning techniques are superior to simpler models like Naïve Bayes in handling sentiment analysis tasks. Even with a small dataset, the high accuracies attained by RF and XGBoost models indicate that these algorithms are suitable for sentiment analysis tasks within the context of Twitter discourse on elections. To achieve accurate sentiment analysis results, model complexity, and algorithm selection play a crucial role, as demonstrated by the comparison with other studies. While ensemble learning techniques like RF and XGBoost offer competitive performance with easier implementation and less computational overhead, deep learning models like CNN-BiGRU may offer slightly higher accuracies.

CONCLUSION

Integrating NLP tasks and ML techniques can strengthen predictive modelling and provide insights into sentiment trends across social media platforms regarding the Nigerian 2023 General Elections. This research concludes that sentiment analysis on Twitter can offer valuable insights and serve as a foundation for election analysis and outcome prediction. Despite Twitter's significance as a platform for political discourse, it is predominantly utilized by a small fraction of the population, with most users passively consuming content rather than actively engaging in discussions. Results from this study reveal that RF and XGBoost algorithms achieve notable accuracy (93%) and precision (96%) in categorizing neutral sentiments, surpassing SVM with 89% accuracy and 93% precision. Additionally, for negative sentiments, RF (94%) and XGBoost (94%) maintain high precision, followed by SVM (86%). These findings suggest a prevalent neutral and negative sentiment surrounding the Nigerian General Elections, warranting careful consideration for future electoral processes.

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